Using Bayesian Analysis to Predict Election Results

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1. Introduction

For as long as I can remember, I have been fascinated by politics, from the power dynamics that have shaped recent history to the magnificent system in which we live, a democracy. Although democracies are not without their flaws, particularly when we consider the current voting system used in Canada, they are arguably the best political system ever created by mankind.

An highly interesting event that results from a democratic election is the night right after where the nation awaits for the final results, slowly receiving updates for the current ballots count for different constituencies. While this is happening, news agencies are trying to use their current data to predict the final results. This process of highly confidently predicting the final results of constantly updating data while trying to make that prediction as soon as possible has long been a source of interrogation for me. Impressively, news agencies are ridiculously fast at forming their predictions, like when Radio-Canada successfully predicted that the Coalition Avenir Québec would form a majority government less than 11 minutes after results started to come in for the Québec 2022 election [15]. Furthermore, although they occasionally make wrong predictions [8], this is exceedingly rare.

In short, I started to wonder about how news agencies could be so fast and so accurate. This paper will be my attempt at building a model to make electoral predictions, so that I can better understand the seemingly magical tools that are used. It is to be noted that my goal here is not to reverse engineer how existing systems work, as I do not have access to the same data that news agencies have. I will instead try to build a simple tool that would allow anyone to simply insert the current ballot counts in their constituency and see the probability that each of the candidates has to win.

The model will based on the "first-past-the-post" election system used in provincial and federal elections in Canada. The Canadian electoral systems generally work in the following way:

1. The territory is divided in smaller districts of similar size in terms of population called *constituencies*.
2. During the elections, electors can go cast a vote for their single favorite candidate in their constituency. Each vote will go in a *box*. Each constituency has multiple boxes of an approximately fixed number of votes.
3. Once all the votes have been gathered, the vote start to be released. This phase can take multiple hours, due to the long process of counting every vote.
4. The results are released box by box.

To verify the accuracy of my model, I will need to compare it to past election data. The data I chose to collect was sampled from Quebecois, Ontarian and Canadian elections (at the provincial or federal level) from the past few years, since those are the elections I have most interacted with, as a Quebecer currently living in Ontario.

Out of all the possible ways to approach such a problem, the one I found the most interesting was to model the situation as a conditional probability problem, as it is a very theorical approach and I was curious to know if it could accurately represent the real world. Other approaches, such as regression or hypothesis testing, would be quite interesting extensions to this paper.

2. Collecting Real-World Data

Before trying to model the situation, we should first gather past data, so that we can test the model with real-world examples while developping it. As we are interested in the partial results (while the ballots are still being counted) of past elections instead of the final results, there is not much publicly available data. Fortunately, Radio-Canada has public archives of all the election nights they streamed on YouTube over the last few years.

This means that we can look at every time a constituency was shown on screen and record the current ballot counts, as well as the number of boxes counted versus the total number of boxes in the constituency.

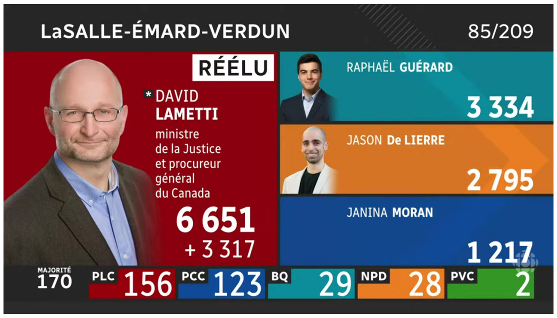

Figure 1: A sample frame from Radio-Canada's presentation of the 2021 federal election [13]

Then, using public records, we can also note which of the candidates really won in the end. Here are the elections I chose to gather data from:

- Canada (Federal), 2019; *Sources: [2], [12]*
- Canada (Federal), 2021; *Sources: [2], [13]*
- Ontario (Provincial), 2022; *Sources: [3], [14]*
- Quebec (Provincial), 2022; *Sources: [4], [15]*

At first, I attempted to collect the data by hand, with custom software to assist me in the menial task. However, I realized that this endeavour would know no ends and that I had to find a better solution. This lead me to fully automate the task using a mix of optical character recognition (OCR) and of color recognition. Although the OCR was not always perfect, my code had several failchecks to make sure the collected data was as reliable as possible. Here are a few caveats about the data collection:

- Only the candidates shown by Radio-Canada are counted. To match this, when looking up the end total vote count, only the top five candidates were considered.[1]
- The OCR could only capture the frames where the data was shown in full screen, which means not all data points were captured.

The full dataset is available in Appendix A.

[1]From my observations, Radio-Canada never displays more than the top five candidates. Furthermore, the candidates not shown by Radio-Canada probably have so little votes that they would have little to no impact on the final results.

3. Analyzing the Data

In the end, the full dataset is 603 rows long and contains data from 228 different constituencies. Here are a few interesting metrics from it vizualized:

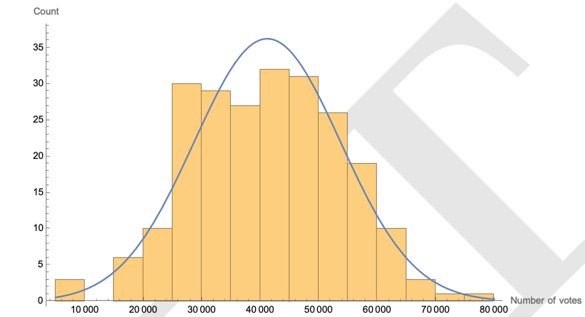

Figure 2: Distribution of the final total vote counts

Figure 2 shows how the total number of votes in a constituency at the end of the election is distributed as an histogram. In orange, we can see how many constituencies reside in each bin. The blue curve shows a normal distribution with the mean and standard deviation of the data (mean of $\mu \approx 43\,476$ and standard deviation of $\sigma \approx 13\,106$), showing that the end total vote count seems to be somewhat normally distributed. This information may come in helpful to evaluate the model, as we should clear prioritize accuracy for constituencies with approximately 40 000 voters.

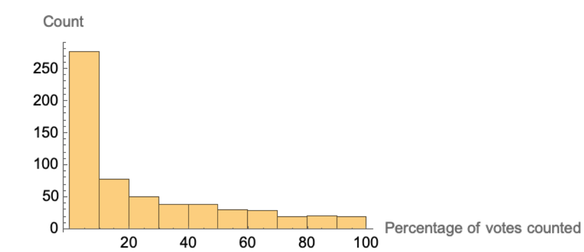

Figure 3: Distribution of the percentages of votes counted

In Figure 3, we can see how the data points are distributed in terms of the percentage of votes that were counted at the moment they were shown by Radio-Canada. We can notice how the vast majority of the data was captured when not many votes had been counted. Once again, in the spirit of building a model to help election-night watchers predict the probability that a certain candidate will be elected, this means that we should prioritize the accuracy of our model for low quantities of votes counted.

To compare our statistical model to real-world data, a plot showing the probability of being elected based on the collected data will be quite useful. However, it is impossible to show all the useful dimensions of our data (the vote count for each of the candidates and the percentage of votes counted) in a single plot, as this would require a 7-dimensional graph (6 for the independent variables and 1 for the dependent variable). Therefore, we need a way to group some of these axes together. The solution I found to this problem is to use the percentage of votes counted and the percentage lead of the leading candidate as axes, as these are arguably the two main intuitive factors when trying to predict if the leading candidate will be elected.

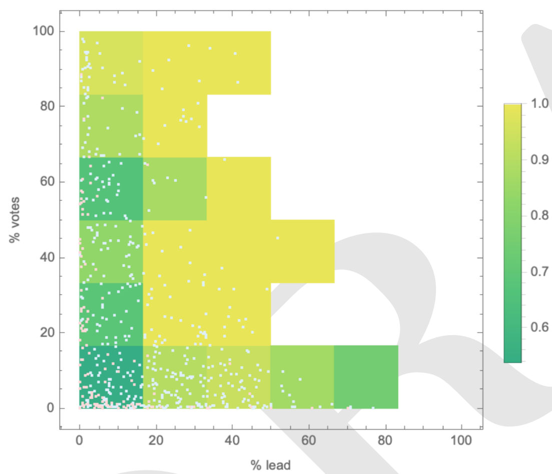

Figure 4: Plot of the collected data

Figure 4 shows exactly this. It was built by first plotting all 603 data points on a plot with the axes described above. These points were then coloured based on wether or not the leading candidate was elected in the end (blue if elected, red if not). The axes where then separated into 6 segments each, creating 36 bins. Finally, the bins were coloured based on the ratio of blue points (situations where the lead won) over the total number of points (total number of situations). For example, if in the upper left bin, there are 28 points, with only one red. This means that out of 28 observed situations with 0 % to 10 % of votes counted and 90 % to 100 % lead, only once did the leading candidate not win. The probability of the leading candidate winning if the situation is in that bin is therefore $\frac{27}{28} \approx 0.9643$, which means the bin will be yellow. The cells that do not contain any points were left white.

This makes this plot a two dimensional histogram of the probability of a lead candidate winning if it lands in a specific bin. So that they can be visually compared, all graphs of this type throughout this exploration will use the same colour scale.

However, we need to keep in mind that the axes used here are not a direct representation of our original data. Our representation taking only the relative difference of the first and second candidate into account, the plot assumes that all the other factors average out. Therefore, it is only reliable when many data points are in bin, which explains why there is some random variation in the colors of the graph. This random variation introduces a source of error when working with our data: the size of the bins (derived from the number of bins) can change the trends we see. The number 36 was chosen here as a tradeoff between having enough bins to observe trends, while having each bin contain quite a few points.

As we can see, for very low percentages of votes counted, there is quite a bit of random variation in the probability of being elected. However, as the percentage of votes and the percentage of lead increases, the probability of the lead being elected increases, just as we would naturally expect. This is represented by the graph being more and more yellow toward the top-right corner.

4. Building the Model

As with any mathematical problem, a considerable portion of building the model is simply to lay down our assumptions and to split the task into multiple, more specific, problems. To approach this using the tools of conditional probability, we first need to understand why predicting election results even involves random events. The fundamental assumption we need to do here, from which all of the mathematics will follow, is that we can consider each individual casting its vote as an independent random event were the different possibilities are the different candidates in the constituency, with each candidate having a different probability of receiving a vote.

Let's unpack this. Essentially, we can imagine that the probability that a voter will vote for a given candidate is the final proportion of votes that that candidate will have received in the final results. Furthermore, each vote would be independent of the other ones, because election results aren't shown until every polling booth is closed.[2]

Let's start by defining a few variables. Let n be the number of candidates in the constituency.

Let $v = \{v_1, v_2, v_3, \ldots, v_n\}$ be the set of the current vote counts for the different candidates, ordered from largest to smallest, where v_1 is the number of votes for candidate 1, $v2$ is the number of votes for candidate 2, etc. And let $v_t = \sum_{i=1}^{n} v_i$ be the total number of votes.

Also, let b_c be the number of ballot boxes counted and b_t be the total number of ballot boxes.

The number of votes left to be counted will also be relevant (if only a few votes are left to be counted, the probability of the lead candidate being elected will be much higher), but it is not a number known in advance. However, we can approximate it by assuming the number of votes per ballot box is roughly constant. Therefore, let $v_e = \frac{b_t}{b_c} v_t$ be the expected end total number of votes, and let $v_l = v_e - v_t$ be the expected number of votes left to count.

In general, when discussing a certain candidate, I will refer to it as the kth-candidate. For example, I consider the candidate k to currently have v_k votes.

As we are working with conditional probability, our beliefs about the probability each candidate has to win will be most often represented by probability distributions. This idea will be detailed below, notably in Section 4.1.

[2] For federal elections, due to the large timezone differences, the results of some of the Eastern provinces are compiled before polls close in some of the Western provinces. However, there is, overall, very little overlap.

Through this paper, our first goal will be to represent the likelihood of observing the evidence we have (the current number of votes) as a function (Section 4.3) and to represent our prior beliefs (what we thought before observing any data about the chances that each candidate has to win) as a probability distribution (Section 4.4). We will then be able to combine those two pieces of information through the use of Baye's theorem, which will give us a probability distribution representing the probability that a certain candidate will have a certain share of the final votes, assuming the election contains infinitely many votes (Section 4.5). Finally, using this and the number of votes left to be counted, we will be able to generate a probability distribution representing the expected final number of votes for a given candidate (Section 4.7). This will give us all the information we need to compute the probability that each of the candidates has to win over the others.

Therefore, we will have $D = \{D_1, D_2, D_3, \ldots, D_n\}$ be the list of the unknown probability distributions representing the probability that a certain candidate will have a certain share of the votes, where D_1 is the probability distribution for the candidate 1, D_2 for the candidate 2, etc.

Finally, $E = \{E_1, E_2, E_3, \ldots, E_n\}$ will represent the list of probability distributions for the final expected number of votes, where E_1 is the distribution for the candidate 1, E_2 for the candidate 2, etc.

Although the sets D and E may look quite cryptic for now, their meaning and utility will become much clearer through the rest of this paper.

Due to the usefulness of specific, visual examples when trying to investigate probability questions, let's use the following variables as a simple and concrete example:

$$n = 5$$
$$v = \{60, 50, 36, 34, 20\}$$
$$v_t = 60 + 50 + 36 + 34 + 20 = 200$$
$$b_c = 10$$
$$b_t = 16$$

$$v_e = \frac{16}{10}(200) = 320$$
$$v_l = 320 - 200 = 120$$

This means that we will be looking at a 5 candidates election (n), where the the leading candidate currently has 60 votes (v_1). Out of the 16 boxes in the constituency (b_t), 10 have been opened (b_c), which allows us to predict that there will be around 320 votes in the end (v_e), based on the 200 we currently have (v_t).

Although this set of data will be used for numerical and graphical example, this paper will not focus on the computation of specific numerical examples, as the endgoal is to have a generalized computer model. Furthermore, due to their nature, many of the computations discussed here have no analytical solutions, which is why computer based approximations will be favoured.

4.1. Probability of probabilities

A reccurant theme in this paper will be the idea of *probability of probabilities*. Although this may seem like an utterly nonsensical statement at first, it is actually at the root of many advanced concepts in conditional probability. In order to explore this idea, let's use an example situation.

Considering a biased coin whose mathematical weight (bias) is unknown, after observing 90 heads and 10 tails out of 100 trials, what should we expect the bias to be?

One might argue that the answer is trivial: to find the weight, we divide the number of observed heads (or tails) by the number of throws. This goes with the idea of the *Law of large numbers* [26] that the more trials we observe, the more the observed frequency will approach the theorical (the real) probability.

However, I would argue that this reasoning is flawed. Yes, $\frac{90}{100} = 0.9$ is the most likely probability, but it is possible that the *true* probability is 0.1, 0.99 or any other value between 0 and 1, exclusively. An event being unlikely does not mean it is impossible.

The better approach is therefore to use probability distributions: instead of trying to define the weight of the coin with a single number, we can define a probability distribution that represents how likely each of the infinitely many possible values of the bias are. That probability distribution would most likely be a beta distribution, which we will explore below.

4.2. Understanding the Beta Distribution

As we will heavily rely on it, it is important that we understand the beta distribution. Two reasons make it ideal for representing probability of probabilities: its domain is $[0, 1]$ and the area under a beta distribution's Probability Density Function (PDF) over its range is 1. This means that any value on the x-axis represents a possible probability and that the y-value of the distribution at that point represents the probability density that that probability is the true one.

Furthermore, the beta distribution can take a variety of shapes, as its PDF is, most commonly, defined in terms of two shape parameters, α and β, both being positive non-null real numbers. It's definition is based on the beta function, here called $\mathcal{B}$ [21]. Let's define a distribution X such that $X \sim \text{Be}(\alpha, \beta)$, where Be is the beta distribution.

$$P(X = x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\mathcal{B}(\alpha, \beta)}, x \in [0, 1]$$

In the definition of the PDF of the beta distribution, $\mathcal{B}$ is the beta function. Dividing by the beta function has the effect of scaling the numerator in order to make the area under the beta distribution's PDF equal to 1. It is therefore equal to the integral of the numerator.

$$\mathcal{B} = \int_0^1 x^{\alpha-1}(1-x)^{\beta-1}\,\mathrm{d}x$$

However, it is more commonly defined as follows, where Γ is the gamma function [22]:

$$\mathcal{B}(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha + \beta)}$$

This distribution would have a mean of [21]:

$$E(X) = \mu_X = \frac{\alpha}{\alpha + \beta}$$

Finally, the gamma function can be viewed as an expansion of the factorials to the Reals (except for integers smaller or equal to 0) while respecting the following identity [24], n being a positive integer, (a more detailed explanation of the gamma function has been deemed outside of the scope of this investigation):

$$\Gamma(n) = (n-1)!$$

The beta distribution will be refered to as $\mathrm{Be}(\alpha, \beta)$ throughout this paper. Here are a few beta distributions plotted, demonstrating some of the various shapes it can take:

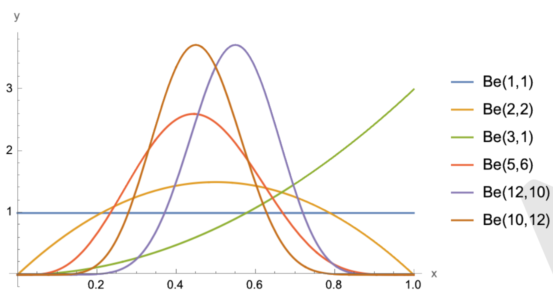

Figure 5: A few beta distributions

In Figure 5, we can see multiple interesting things, notably that a $\mathrm{Be}(1,1)$ distribution is equivalent to a $\mathrm{Uniform}(0,1)$ distribution [28][3] and that the beta distribution can be both symmetric and highly asymmetric about the average.

Finally, the Cumulative Distribution Function [18] (CDF) of a beta distribution is the regularized beta function [27], notated $\mathcal{I}(z; a, b)$, which is in itself expressed in terms of the incomplete beta function [25], notated $\mathcal{B}(z; a, b)$.[4]

$$P(A \leq z) = \mathcal{I}(z; \alpha, \beta) = \frac{\mathcal{B}(z; \alpha, \beta)}{\mathcal{B}(\alpha, \beta)}$$

Now that we understand the beta distribution, we can go back to building the model.

[3] A uniform distribution is a distribution where all values in a given interval (in this case, $[0,1]$) are equally likely.

[4] A deeper exploration of the regularized and incomplete beta functions not being relevant to the rest of the mathematics, I will not explore them in greater details.

4.3. Building the Likelihood Function

The first step is to figure out the probability distribution representing the share of votes each candidate has.

Seeing this from the persepective of each of the candidates, we can consider the number of votes received over the total number of votes as a binomial experiment, where a *success* is defined as a vote for that candidate and a *failure* as a vote given to any other. As a reminder, the Probability Mass Function [11] (PMF), the discrete analogue of the PDF [11], for a binomial distribution Y, $Y \sim \mathrm{B}(m, p)$[5], would be the following, where p is the probability of the event happening and m is the total number of trials:

$$P(Y = x) = \binom{m}{x} p^x (1-p)^{m-x}, x \in \{0, 1, 2, \ldots, m\}$$

In our case, we know both the number of successful trials, v_k, (the current number of votes for the candidate) and the total number of trials, v_t, (the current total number of votes). This means that, for the candidate k, with number of votes v_k, the unknown left is the probability, here p, of receiving a vote distributed from the unknown distribution D_k, D_k being the distribution representing the probability that the candidate will receive the next vote. We can therefore rewrite the above equation by building a binomial distribution $V_k \sim \mathrm{B}(v_t, p)$.

$$P(V_k = v_k \mid D_k = p) = \binom{v_t}{v_k} p^{v_k} (1-p)^{v_t - v_k}$$

However, as the distribution V_k is not really important, we could also represent the above as follows,

$$P(v_k \mid D_k = p) = \binom{v_t}{v_k} p^{v_k} (1-p)^{v_t - v_k}$$

meaning: *What is the probability of observing the evidence v_k given that $D_k = p$?*

As what really interests us is the unknown distribution D_k, we can rewrite this as its likelihood function [20], $L_{D_k}(p)$, which will answer the question: *Based solely on the evidence, how likely is it that a*

[5] Here, m is used instead of the typical n in order to avoid confusion with the number of candidates in the constituency.

certain value of the probability p is the true probability that lead to the observed events?

$$L_{D_k}(p) = P(v_k \mid D_k = p)$$
$$= \binom{v_t}{v_k} p^{v_k} (1-p)^{v_t - v_k}$$

Here is the plot of this function for the leading candidate ($k = 1$) in our example, considering it currently has $v_k = v_1 = 60$ and that the total number of votes is $v_t = 200$:

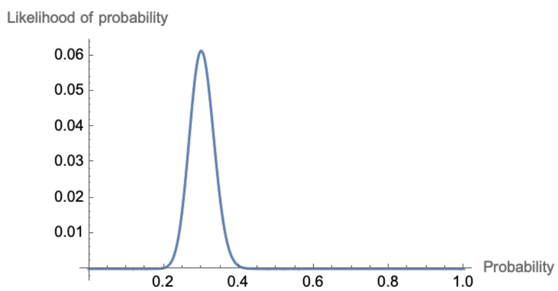

Figure 6: Plot of the likelihood function for the leading candidate

Referring back to Section 4.1, this is an example of a probability distribution representing an unknown probability. We should however still expect the mode of our distribution, its maximum, to be the simple frequency calculation $\frac{v_1}{v_t} = \frac{60}{200} = 0.3$, which we can verify in Figure 6.

However, we are still missing a key element before being able to say that this function represents the probability distribution of the share of the votes a given candidate has, as we still need to consider our prior beliefs [20].

4.4. Building Prior Beliefs

Our prior beliefs, as the name implies, is what we believe the probability distribution to be before seeing the evidence (the partial election results, in our context). We express it in the form of a probability distribution. In our context, there are two ways we can approach this: prior ignorance and substantial prior knowledge [7]. This process of quantifying our prior beliefs is often referred to as prior elicitation [6].

Prior ignorance is really quite easy: we assume we know nothing before the election. Therefore, we need a distribution illustrating that we consider all probabilities to be equally likely. This is the perfect use for the uniform distribution, so we would say that our prior beliefs about the probability distribution of the share of the votes of a given candidate (D_k) follows a Uniform$(0, 1)$ distribution (also known as a Be$(1, 1)$ distribution).

Substantial prior knowledge is quite a bit less trivial. First, let's define exactly what it means. Commonly, we will say we have substantial prior knowledge "[when] expert opinion, for example, gives us good reason to believe that some values in a permissable range for [p] are more likely to occur than others." [6] In our case, expert opinions could be the polls from firms like Léger, who usually publish there results a few weeks before any major election. An example of such a report could be Léger's *Élections provinciales : Montréal et Laval* [9], which contains two key pieces of information:

- The voting intentions (what percentage of people plan to vote for each of the parties).
- The firmness of the intentions (for each party what percentage of people don't expect to change their minds).

For example, suppose we knew from a report that 35% of the citizens intended to vote for a given party, and that 45% of those people are quite firm about their decision, how could we transform this into a probability distribution? For the reasons outlined in Section 4.2, it seems reasonable to try building a beta distribution. Let's therefore define our prior beliefs distribution as $U \sim \text{Be}(\alpha, \beta)$.

First, we know that our expected value (the mean of the distribution) should be 35 % (0.35). Then we could define "quite firm" as being at ±5% of the mean. The probability of landing in that range must therefore be equal to 45 % (0.45). This is equivalent to stating that the area under the PDF of our distribution in the range $[0.30, 0.40]$ should be equal to 0.45. Let's write a system of equation using both of these facts:

$$0.35 = E(U)$$
$$= \mu_U$$

$$= \frac{\alpha}{\alpha + \beta}$$

And

$$0.45 = \int_{0.30}^{0.40} P(U = x)\,\mathrm{d}x$$
$$= \int_{0.30}^{0.40} \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\mathcal{B}(\alpha, \beta)}\,\mathrm{d}x$$

We should also keep in mind that both α and β need to be positive to satisfy the requirements of the beta function. As there is no trivial analytical solution to this system of equations, the most efficient solution is to resort to numerical approximation to solve for α and β. It is to be noted that this system of equations may not always yield a solution when considering extreme requirements, like having a exceedingly small margin arround the mean for the definition of "quite firm". This, however, is not really an issue as these cases would lead to such certain prior beliefs that any evidence would hardly be relevant.

Using Wolfram Mathematica [30] or similar software, we can find that this system is solved by $\alpha \approx 11.485$ and $\beta \approx 21.330$. This gives us the folowing probability distribution as our prior beliefs:

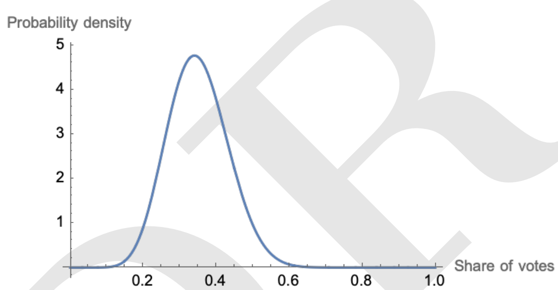

Figure 7: Plot of the probability distribution built from prior knowledge

It is important to keep in mind that this process is quite subjective. In fact, we chose to define "quite firm" as being $\pm 5\%$ of the mean, but we could have chosen $\pm 7\%$, $\pm 3\%$ or any other value. This is the main weakness of this process: our biases can easily sneak into our statistics if we are not careful.

As our prior beliefs can be represented as a beta distribution no matter if we have prior ignorance or prior substantial knowledge, it makes sense to define our prior beliefs for the candidate k as $D_k \sim \mathrm{Be}(a_k, b_k)$ before seeing any of the evidence. For the rest of this investigation, all of our prior knowledge about the candidate k will be referred to with the variables a_k and b_k shaping this distribution. We can now write our prior beliefs as follows:

$$P(D_k = p) = \frac{p^{a_k - 1}(1-p)^{b_k - 1}}{\mathcal{B}(a_k, b_k)}$$

4.5. Combining Prior Beliefs and Likelihood

Now that we know how to form our prior beliefs and our likelihood function, it is time to combine them into the probability distribution for the share of votes of a candidate.

This is where Bayes' theorem comes in. In fact, this theorem gives a systematic method to mix prior beliefs and observed evidence (summarized into the likelihood function) into posterior beliefs.[6] As a reminder, here is the formula for said theorem [19], where A and B are independent random events:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

However, I dislike this depiction of Bayes' theorem as it abstracts and hides its true beauty. Exploring each of the terms leads us to the following:

$P(A \mid B)$ This represents our *posterior beliefs* about A, considering that B happened.

$P(B \mid A)$ This represents the *likelihood* that A happens given the observed evidence for B.

$P(A)$ This represents our *prior beliefs* about A.

$P(B)$ This represents the total probability of B. Essentially, this has the effect of scaling the probability of $A|B$ such that it lands between 0 and 1. In the case of probability distributions, this ensures that the area under the distribution's curve equals 1 [5].

It is also interesting to note that $P(B \mid A)$ and $P(A)$ can not only be probabilities, but also probability distributions, making $P(A \mid B)$ into one too.

As $P(B)$ is simply a scaling constant, we can rewrite

[6] A justification for Bayes' theorem has been deemed outside of the scope of this investigation.

this formula as

$$P(A \mid B) \propto P(B \mid A)P(A)$$

However, I believe that the following is a much more elegant way to describe Bayes' theorem [5]:

$$\text{posterior} \propto \text{likelihood} \times \text{prior}$$

The beauty of this lies in how clearly it highlights how evidence (likelihood) doesn't replace our prior beliefs, but rather updates them to form our posterior beliefs [16].

But how could we apply this to our variables? Let's rewrite this in terms of our variables and explore each of the terms, keeping in mind $p \in [0, 1]$:

$$P(D_k = p \mid v_k) \propto P(v_k \mid D_k = p)P(D_k = p)$$

$P(D_k = p \mid v_k)$ This is the probability distribution D_k (as a function of p) we are searching for.

$P(v_k \mid D_k = p)$ This is the likelihood function we derived earlier, $L_{D_k}(p)$.

$P(D_k = p)$ This is the prior beliefs distribution we derived earlier.

As we can see, all of our work is really coming in together. Let's substitute the terms with our findings from the previous subsections.

$$\begin{aligned} P(D_k = p \mid v_k) &\propto P(v_k \mid D_k = p)P(D_k = p) \\ &\propto \left(\binom{v_t}{v_k} p^{v_k} (1-p)^{v_t - v_k} \right) \\ &\quad \left(\frac{p^{a-1}(1-p)^{b-1}}{\mathcal{B}(a, b)} \right) \\ &\propto \left(p^{v_k}(1-p)^{v_t - v_k}\right)\left(p^{a-1}(1-p)^{b-1}\right) \\ &\propto p^{v_k + a - 1}(1-p)^{v_t - v_k + b - 1} \end{aligned}$$

There are three things to notice and recall here: (I) As this distribution represents possible values of a probability p, it's domain is $[0, 1]$. (II) As with any other continuous probability distribution, its area over its range (here, $[0, 1]$) must be equal to 1. (III) The beta distribution matches both the form of the equation we obtained and the above two criterias.

Finding the beta distribution corresponding to our above equation is simply a question of identifying the values of the unknown parameters. In a beta distribution $\text{Be}(\alpha, \beta)$ whose PDF is expressed as a function of x, x is raised to the power of $\alpha - 1$ and $1 - x$ is raised to the power of $\beta - 1$. Applying this to our example, where the distribution is expressed in function of p, we get the following coefficients and, therefore, the following distribution:

$$\alpha - 1 = v_k + a_k - 1$$
$$\alpha = v_k + a_k$$

And

$$\beta - 1 = v_t - v_k + b_k - 1$$
$$\beta = v_t - v_k + b_k$$

Therefore

$$D_k \mid v_k \sim \text{Be}(v_k + a_k, v_t - v_k + b_k)$$

Sadly, as detailed polls for elections dating back multiple years are not trivial to find, we will have to assume prior ignorance for the evaluation part of this investigation. Remembering that prior ignorance can be represented as a $\text{Be}(1, 1)$ distribution, we know that both a_k and b_k would be equal to 1 in this scenario. The following expression therefore represents our posterior beliefs when we lack substantial prior knowledge.

$$D_k \mid v_k \sim \text{Be}(v_k + 1, v_t - v_k + 1)$$

The process of deriving prior beliefs, observing evidence to build a likelihood function and combining those two elements together is commonly referred to as *bayesian analysis* [20], hence the name of this paper.

As a reminder, D_k is the distribution representing the probability that the candidate k will receive the next vote, which is equivalent to the share of votes it would get if the election was to run infinitely.

For the sake of visual understanding, let's visualize our findings for each of the candidates in our example.

It is interesting to note that both our prior and posterior beliefs are beta distribution when the likeli-

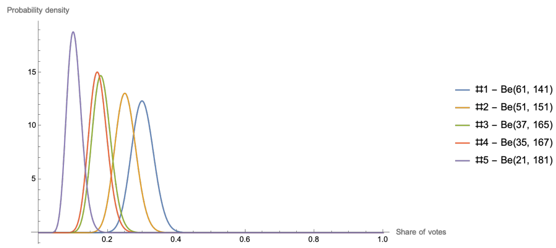

Figure 8: The set of distributions D

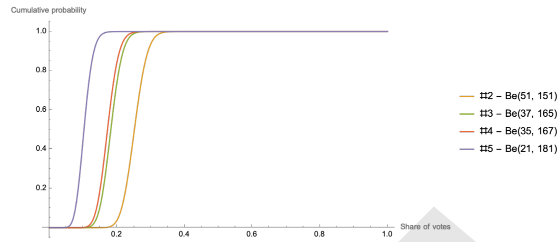

Figure 9: The CDFs of the distributions D for all but the leading candidate

hood function comes from a binomial distribution. In bayesian analysis terminology, we would describe this by saying that the beta distribution is a conjugate prior for the binomial distribution [10].

4.6. Comparing Probability Distributions

In Figure 8, we can see that, just as we would expect, the more votes a candidate currently has, the more likely it is to have a larger share of the votes. For example, the candidate with the most votes, candidate 1, is associated with the rightmost distribution, while the candidate with the least votes, candidate 5, is associated with the leftmost distribution.

However, we still don't have the concrete probability that each candidate has to win. For now, let's assume that elections are infinite and that winning means having the greatest share of votes in the long run.[7] This would mean that a candidate's probability to win is the probability that its probability distribution from the D is "bigger" than all the other candidates' distributions. But what exactly does "bigger" mean here? And how could we quantify it? For the following steps, visual examples will be crucial. Let's use the leading candidate as our example.

First, let's consider the probability that some candidate k will have less than a certain share r of the votes, $P(D_k \leq r)$[8]. Plotting this for all candidates except the leading one gives us Figure 9.

As all of our distributions come from independent events, we can find the probability that all these four distributions will be smaller than r by simply multiplying them together. Plotting this leads to Figure 10.

[7]This assumption will be revisited in Section 4.7.

[8]As we are working with continuous distributions, $P(D_k \leq r)$ is equivalent to $P(D_k < r)$.

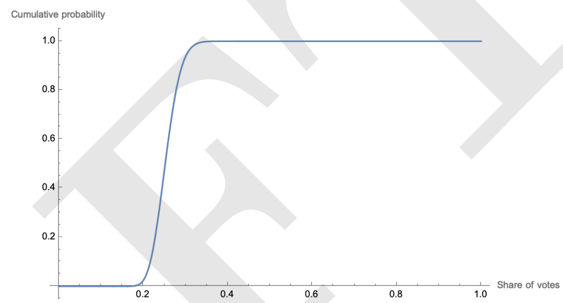

Figure 10: The product of the CDFs of the distributions D for all but the leading candidate

From the distribution of the leading candidate, D_1, we know the probability that it will have some share r of the votes. Therefore, keeping in mind we are working with independent events, we can find the probability that all other candidates will have a share smaller than r (what we see in Figure 10) and that the leading candidate will have that share of the votes (D_1's PDF evaluated at r) by simply multiply them together.

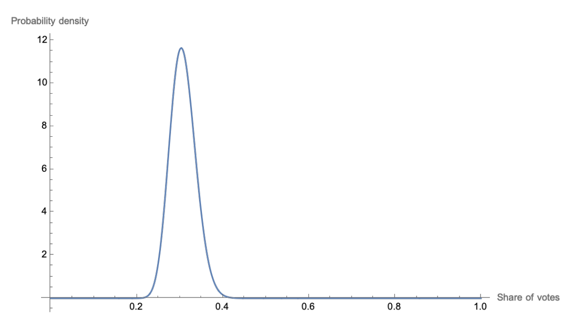

Figure 11: Probability that the leading candidate at any given share of the votes

Finally, we can get the total probability that the leading candidate will have a bigger share of votes than all the other candidates by calculating the area under the above curve over the course of its domain.

This would yield that the leading candidate has a probability of approximately 0.86658 of winning. Doing the calculations for all the candidates gives us approximately the following results: (1) 0.86658 (2) 0.13183 (3) 0.00012 (4) 0.00004 (5) 0.00000.

A simple verification we can do to ensure our mathematical reasoning was not blatantly wrong is simply to add the above numbers and verify they add up to 1, as we know that a candidate will be elected (the probability of any candidate being elected is the sum of the probability of each candidate to be elected), which they do.[9] In other words, the probability that a candidate will win is mutually exclusive and complementary to the probability that any of the other candidates will.

An important question left unanswered is why was the area under the curve not 1. Of course, we know intuitively that this couldn't be the case, but all other continous probability distributions encountered in this paper had an area of 1, leading to the question: *What is different here?* What they all had in common is that they considered *how* an even that we know will happen would happen. However, here, the candidate is not certain to win, which is why the total probability of it winning, the area under the curve, is less than one.

Let's summarize the steps we did in a more general form, assuming we are searching for the probability that a candidate k will win. First, we multiplied the probability that all other candidates would have a share smaller than r of the votes.

$$\prod_{\substack{i=1 \\ i \neq k}}^{n} P(D_i \leq r)$$

Then, we multiplied that expression by the probability that the candidate k would have that share r of the votes.

$$P(D_k = r) \prod_{\substack{i=1 \\ i \neq k}}^{n} P(D_i \leq r)$$

[9]Adding the numbers displayed here leads to finding 1.00001 as the sum instead. This deviation is simply due to the fact that the numbers were calculated with more significant figures than displayed here.

Finally, we took the area under the curve.

$$\int_{-\infty}^{\infty} P(D_k = r) \prod_{\substack{i=1 \\ i \neq k}}^{n} P(D_i \leq r) \, \mathrm{d}r$$

However, since D_k is a beta distribution, $P(D_k = r)$ is 0 for all values outside of the interval $[0, 1]$ and we can therefore limit the bounds of the integral.

$$\int_{0}^{1} P(D_k = r) \prod_{\substack{i=1 \\ i \neq k}}^{n} P(D_i \leq r) \, \mathrm{d}r$$

More generally, the following is the formula for calculating the probability that a certain probability distribution X_k will have a greater value than all other distributions in the set X, containing n elements, considering the PDF of the distribution X_k has non-zero values only in the interval $[a, b]$. This expression is largely inspired from *What is $P(X_1 > X_2, X_1 > X_3, \ldots, X_1 > X_n)$?* [29][10].

$$P\left(\bigcap_{i=1}^{n} X_k \geq X_i\right) = \int_{a}^{b} P(X_k = x) \prod_{\substack{j=1 \\ j \neq k}}^{n} P(X_j \leq x) \, \mathrm{d}x$$

It is to be noted that there is no analytical solution to the above equations for sets of distributions that contain more than two elements [29]. Therefore, numerical integration will be needed in order to find the probability that a certain candidate will win.

4.7. Considering the Number of Votes Left

Up to here, we assumed some sort of infinite election where a candidate won if the distribution of his share of the votes in the long run was bigger than the one of all the other candidates. However, in a real world election, there is a fix number of votes. But how could we take this into account?

What we first need to know is the probability that a certain candidate will gain a certain number of votes over the number of votes left, v_l. As we may notice,

[10]Although it originally came from a mathematics discussion forum, I believe I have provided a sufficient justification for this formula.

this looks quite a bit like a binomial experiment: (I) we have a fix number of trials (the number of votes left) (II) we have only two possible states for each trial (*success* being the candidate gaining a vote and *failure* being another candidate gaining it) (III) each trial has the same probability of having a specific outcome.

The only problem is that we do not have a probability of gaining a vote, but rather a probability distribution, $D_k \mid v_k$ (for the candidate k). Although this may seem like an issue, it actually isn't. What we need to do is to combine the binomial distribution described above to our probability distribution $D_k \mid v_k$ into a combined *predictive distribution*. In our case, because we have a beta distribution and a binomial distribution, the distribution we will obtain will be a beta-binomial distribution [17], notated here $\mathrm{BetaBin}(\alpha, \beta, m)$, where α and β are the parameters of the underlying beta distribution and m is the number of trial[11].

The following demonstration of the combination of both distributions is a more detailed version of the one included in *Bayesian Statistics, Simulation and Software — The Beta-Binomial Distribution* [1]. The first step is to find the *simultaneous distribution* of the beta and binomial distributions. This means weighing the binomial distribution, $X \sim \mathrm{B}(m, p)$, as a function of the probability p, by the probability that the beta distribution, $Y \sim \mathrm{Be}(\alpha, \beta)$, will equal p. This process is extremely similar to what we did when trying to form our posterior beliefs from a binomial likelihood and a beta prior.

$$
\begin{aligned}
P(X = x \mid Y = p) &= P(X = x) P(Y = p) \\
&= \left(\binom{n}{x} p^x (1-p)^{n-x} \right) \\
&\quad \left(\frac{p^{\alpha-1}(1-p)^{\beta-1}}{\mathcal{B}(\alpha, \beta)} \right) \\
&= \frac{\binom{n}{x}}{\mathcal{B}(\alpha, \beta)} p^{x+\alpha-1}(1-p)^{n-x+\beta-1}
\end{aligned}
$$

Then, we can find the predictive distribution, what we are actually searching for, by integrating the above over the range of p, $[0, 1]$.

$$
\begin{aligned}
P(X = x) &= \int_0^1 \frac{\binom{n}{x}}{\mathcal{B}(\alpha, \beta)} p^{x+\alpha-1}(1-p)^{n-x+\beta-1} \, \mathrm{d}p \\
&= \frac{\binom{n}{x}}{\mathcal{B}(\alpha, \beta)} \int_0^1 p^{x+\alpha-1}(1-p)^{n-x+\beta-1} \, \mathrm{d}p
\end{aligned}
$$

We may recognize from Section 4.2 that the integral we are left with is the denominator of the PDF of a beta distribution $\mathrm{Be}(x + \alpha, n - x + \beta)$, which can be expressed in terms of the beta function, as follows:

$$
\begin{aligned}
P(X = x) &= \frac{\binom{n}{x}}{\mathcal{B}(\alpha, \beta)} \int_0^1 p^{x+\alpha-1}(1-p)^{n-x+\beta-1} \, \mathrm{d}p \\
&= \frac{\binom{n}{x}}{\mathcal{B}(\alpha, \beta)} \mathcal{B}(x + \alpha, n - x + \beta) \\
&= \binom{n}{x} \frac{\mathcal{B}(x + \alpha, n - x + \beta)}{\mathcal{B}(\alpha, \beta)}
\end{aligned}
$$

Considering this, we can now find an expression for the probability that the candidate k will receive a certain number of votes over the rest of the counting process, using v_l as the number of trials and the parameters from $D_k \mid v_k$, the probability for the kth-candidate to receive the next vote, for the underlying beta distribution.

$$
E_k \mid v_k \sim \mathrm{BetaBin}(v_k + a_k, v_t - v_k + b_k, v_l)
$$

Plotting this distribution for each of the candidates gives us Figure 12.

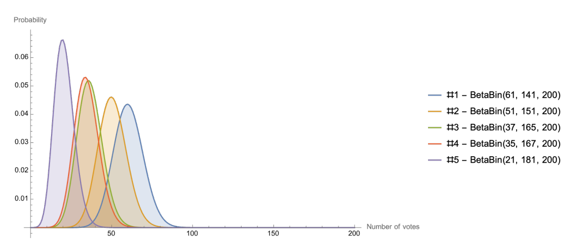

Figure 12: The set of distributions E

Carrying forward, I will notate the PDF of the distribution $E_k \mid v_k$ using functional notation to facilitate the representation of the operations we need to do on it. Therefore, we currently have the following:

$$
\begin{aligned}
E_k(x) &= \binom{v_l}{x} \frac{\mathcal{B}(x + v_k + a_k, v_l - x + v_t - v_k + b_k)}{\mathcal{B}(v_k + a_k, v_t - v_k + b_k)} \\
&= \binom{v_l}{x} \frac{\mathcal{B}(x + v_k + a_k, v_e - x - v_k + b_k)}{\mathcal{B}(v_k + a_k, v_t - v_k + b_k)}
\end{aligned}
$$

[11] Here, m is used instead of the typical n in order to avoid confusion with the number of candidates in the constituency.

Comparing these probability distributions, however, would not be the full story. In fact, we not only want to take into account the number of votes each candidate is expected to get, but also the current number of votes of each candidate. This can be done by translating the above function to the right by the candidate's current number of votes, v_k. The set of the translated distributions will be referred to as E_t and the distribution of the candidate k as E_{tk}.

$$\begin{aligned} E_{tk}(x) &= E_k(x - v_k) \\ &= \binom{v_l}{(x - v_k)} \frac{\left(\begin{array}{r}\mathcal{B}((x - v_k) + v_k + a_k, \\ v_e - (x - v_k) - v_k + b_k)\end{array}\right)}{\mathcal{B}(v_k + a_k, v_t - v_k + b_k)} \\ &= \binom{v_l}{x - v_k} \frac{\mathcal{B}(x + a_k, v_e - x + b_k)}{\mathcal{B}(v_k + a_k, v_t - v_k + b_k)} \end{aligned}$$

An important fact to keep in mind is that E_k, and therefore E_{tk}, are discrete probability distributions. The problem with this is that discrete probability distribution are much harder to compute than continous ones. This is because modern computational mathematics engine, like Wolfram Mathematica [30] have many more tricks to optimize integrals (used in continuous distributions) than sums (used in discrete distributions). Furthermore, the formula derived in Section 4.6 to compare probability distributions is only built for continous distributions, which would mean we couldn't use it to compare our distributions for the expected final number of votes.

The good news is that the beta-binomial distribution, $\mathrm{BetaBin}(\alpha, \beta, n)$, can be computed for non-integer values, as all the functions and operations it depends on also are.

First, the choose function has a continuous expansion, which can be expressed as follows [23].

$$\binom{x}{y} = \begin{cases} 0 & y < 0 \\ \dfrac{\Gamma(x+1)}{\Gamma(y+1)\Gamma(x-y+1)} & 0 \le y \le x \\ 0 & x < y \end{cases}$$

Although it is common not to set restrictions on this expression, I believe they keep the function closer to its original meaning, which is useful in our context, as we still want the idea that it is impossible (value of 0) to have less than 0 votes or more than the maximum.

Second, the beta function is perfectly well defined for both integer and non-integer values, except for nonpositive integers. However, when examining each of the parameters of the beta functions in our expression, we can realize that they will never be nonpositive as long as the number of votes we are considering is between the current number of votes, v_k, and the maximum number of votes the candidate could get, $v_k + v_l$, keeping in mind that a_k and b_k will always be greater than 0, due to restrictions on the parameters of the beta function.

$\boldsymbol{x + a_k \le 0}$ This implies that $x \le -a_k$, but it makes no sense to consider the probability that a certain candidate will *lose* votes.

$\boldsymbol{v_e - x + b_k \le 0}$ This implies that $x \ge v_e + b_k$. However, it doesn't make sense to consider the probability that a candidate will have more votes than are expected in the end for all canidates.

$\boldsymbol{v_k + a_k \le 0}$ This implies that $v_k \le -a_k$, but a candidate will always have a non-negative vote count.

$\boldsymbol{v_t - v_k + b_k \le 0}$ This implies that $v_k \ge v_t + b_k$, but it is not possible for a candidate to have more votes than the total amount.

For impossible number of votes, the most logical thing is to define our function as having a value of 0, to indicate the impossibility of such an event happening.

The continous version of E_{tk} and the continous version of the set E_t will be respectively denoted E_{tck} and E_{tc}. Using this, we currently have the following expression.

$$E_{tck}(x) = \begin{cases} 0 & x < v_k \\ \binom{v_l}{x - v_k} \frac{\mathcal{B}(x + a_k, v_e - x + b_k)}{\mathcal{B}(v_k + a_k, v_t - v_k + b_k)} & v_k \le x \le v_k + v_l \\ 0 & v_k + v_l < x \end{cases}$$

All of this, however, introduces the strange idea of our candidates having non-integer vote counts. The important thing to realize is that this doesn't affect the shape of the distribution, as we are not changing the underlying function[12], which means that we will

[12] Although there are functions that behave oddly at non-integer values, the above expression works as we would expect a continuous interpolation to do. This is shown later in Figure 13.

still be able to meaningfully compare them.

If we are to consider $E_{tk}(x)$ for non-integer values of x, there is one last problem we need to fix. Whereas continous probability distributions use area to determine probability, discrete ones use sums. This means that we need to rescale $E_{tck}(x)$ to ensure the area under its PDF in the interval $[v_k, v_k + v_l]$ (the interval on which it is non-zero) is equal to 1, instead of its sum at integer values. This can be achevied by dividing the function by its integral on that interval. For the sake of clarity, the following demonstration will assume $x \in [v_k, v_k + v_l]$ because it is the only part of the function which will be affected by the rescaling.

$$\begin{aligned}
E_{tck}(x) &= \frac{E_{tk}(x)}{\int_{v_k}^{v_k+vl} E_{tk}(t)\,\mathrm{d}t} \\
&= \frac{\binom{v_l}{x-v_k}\frac{\mathcal{B}(x+a_k,v_e-x+b_k)}{\mathcal{B}(v_k+a_k,v_t-v_k+b_k)}}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\frac{\mathcal{B}(t+a_k,v_e-t+b_k)}{\mathcal{B}(v_k+a_k,v_t-v_k+b_k)}\,\mathrm{d}t} \\
&= \frac{\binom{v_l}{x-v_k}\mathcal{B}(x+a_k,v_e-x+b_k)}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\mathcal{B}(t+a_k,v_e-t+b_k)\,\mathrm{d}t} \\
&\quad\cdot\frac{\left(\frac{1}{\mathcal{B}(v_k+a_k,v_t-v_k+b_k)}\right)}{\left(\frac{1}{\mathcal{B}(v_k+a_k,v_t-v_k+b_k)}\right)} \\
&= \frac{\binom{v_l}{x-v_k}\mathcal{B}(x+a_k,v_e-x+b_k)}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\mathcal{B}(t+a_k,v_e-t+b_k)\,\mathrm{d}t} \\
&= \frac{\binom{v_l}{x-v_k}\frac{\Gamma(x+a_k)\Gamma(v_e-x+b_k)}{\Gamma((x+a_k)+(v_e-x+b_k))}}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\frac{\Gamma(t+a_k)\Gamma(v_e-t+b_k)}{\Gamma((t+a_k)+(v_e-t+b_k))}\,\mathrm{d}t} \\
&= \frac{\binom{v_l}{x-v_k}\Gamma(x+a_k)\Gamma(v_e-x+b_k)}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\Gamma(t+a_k)\Gamma(v_e-t+b_k)\,\mathrm{d}t} \\
&\quad\cdot\frac{\left(\frac{1}{\Gamma(v_e+a_k+b_k)}\right)}{\left(\frac{1}{\Gamma(v_e+a_k+b_k)}\right)} \\
&= \frac{\binom{v_l}{x-v_k}\Gamma(x+a_k)\Gamma(v_e-x+b_k)}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\Gamma(t+a_k)\Gamma(v_e-t+b_k)\,\mathrm{d}t}
\end{aligned}$$

As a reminder, v_k is the number of votes of the candidate k, with a_k and b_k being the parameters of the beta distribution representing our prior beliefs about its share of the votes.

Keeping in mind the domain restrictions on the above expression, the following is the actual function:

$$E_{tck}(x) = \begin{cases} 0 & x < v_k \\ \frac{\binom{v_l}{x-v_k}\Gamma(x+a_k)\Gamma(v_e-x+b_k)}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\Gamma(t+a_k)\Gamma(v_e-t+b_k)\mathrm{d}t} & v_k \le x \le v_k + v_l \\ 0 & v_k + v_l < x \end{cases}$$

In the above, the goal was to simplify the expression not visually, but computationnaly. Later, to verify the accuracy of our model, we will need to run it somewhere between a few thousand and arround a million times. Why this is needed will be detailed then. This means that the computations we are doing need to be as quick as possible. To do so, I have taken out as many constants as possible from inside the integrals and simplified terms that cancelled out in the beta function, even though this arguably lead to a quite verbose expression.

Plotting this continuous and translated set of distributions gives us Figure 13.

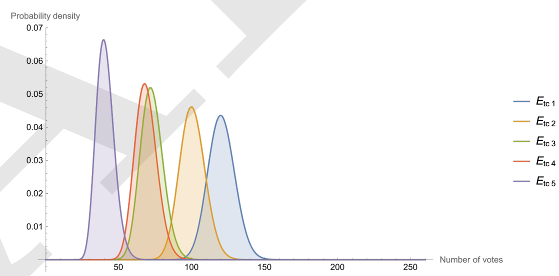

Figure 13: The set of distributions E_{tc}

As we can see, the distributions have now been translated by the candidates' current vote counts. Furthethermore, just as we would expect, there is verry little difference in the shape of each distribution, because our discrete plots already had so many points that they looked continuous. The only noticeable change is the scale, due to the rescaling we did above.

We now finally have a set of continous probability distributions taking into account the current vote counts and the number of votes left to be counted. However, before using the formula derived in Section 4.6, we also need to find the CDF of E_{tck}

Once again, the only relevant interval is $[v_k, v_k + v_l]$, as the cumulative probability of having less than the current amount of votes is 0 and the cumulative probability of having more than the possible amount of votes is 1. Therefore, let's assume this range for the following demonstration.

$$
\begin{aligned}
P(E_{ctk} \leq x) &= \int_{v_k}^{x} E_{tck}(r)\,\mathrm{d}r \\
&= \int_{v_k}^{x} \frac{\binom{v_l}{r-v_k}\Gamma(r+a_k)\Gamma(v_e-r+b_k)}{\left(\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\Gamma(t+a_k)\,\Gamma(v_e-t+b_k)\,\mathrm{d}t\right)}\,\mathrm{d}r \\
&= \frac{\int_{v_k}^{x}\binom{v_l}{r-v_k}\Gamma(r+a_k)\Gamma(v_e-r+b_k)\,\mathrm{d}r}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\Gamma(t+a_k)\Gamma(v_e-t+b_k)\,\mathrm{d}t}
\end{aligned}
$$

Including the restrictions, the full definition of the CDF of E_{ctk} would therefore be the following:

$$
P(E_{ctk} \leq x) = \begin{cases} 0 & x < v_k \\ \frac{\int_{v_k}^{x}\binom{v_l}{r-v_k}\Gamma(r+a_k)\Gamma(v_e-r+b_k)\mathrm{d}r}{\int_{v_k}^{v_k+vl}\binom{v_l}{t-v_k}\Gamma(t+a_k)\Gamma(v_e-t+b_k)\mathrm{d}t} & v_k \leq x \leq v_k+v_l \\ 1 & v_k+v_l < x \end{cases}
$$

Remembering the equation from Section 4.6, we can now replace the terms with the expressions we found in this section.

$$
P\left(\bigcap_{i=1}^{n} X_k \geq X_i\right) = \int_a^b P(X_k = x)\prod_{\substack{j=1\\ j\neq k}}^{n} P(X_j \leq x)\,\mathrm{d}x
$$

$$
P\left(\bigcap_{i=1}^{n} E_{tck} \geq E_{tci}\right) = \int_{v_k}^{v_k+v_l} P(E_{tck} = x)\prod_{\substack{j=1\\ j\neq k}}^{n} P(E_{tcj} \leq x)\,\mathrm{d}x
$$

So, here it is. After all this work, we finally have a computable expression for the probability a candidate has of winning. As we can see, it uses the PDF of the candidate whose probability of winning we are searching for and the CDFs of the other candidates.

Using this formula with our example would give us the following predictions.

Table 1: Predictions from first and second model

Candidate #	Section 4.6	Section 4.7
1	0.86658	0.96604
2	0.13183	0.03395
3	0.00012	0.00000
4	0.00004	0.00000
5	0.00000	0.00000

As we can see, the predictions change quite a bit once we account for the number of votes left. The probability of the first candidate winning has increased by arround 10 percentage points, decreasing the probability of other candidates winning. This makes sense, because the leading candidate not only has a higher probability of gaining a vote than his opponents, but also because it doesn't need to catch up to anyone.

It is to be noted that this expression is exceedingly expansive to compute, as it necessitates the integral of the product of $(n-1)$ integrals for an n-party election, sometimes taking upwards of 1 min, even on a modern computer, for a single candidate. A quicker way to approximate it would therefore be an highly interesting extension to this paper.

5. Analyzing the Model

Now that we have a model, it would be most useful to be able to generate a plot in the same style and configuration as the one we used to visualize our collected data, seen in Figure 4.

As a reminder, what we have is a two-dimensional histogram showing the probability of the leading candidate winning if it lands in a given bin of percentage of votes counted and percentage lead. Also, it is important to remember that our data actually has 6 axes (the percentage of votes counted and the number of votes for each of the five candidates), which are indirectly reflected in the two we have chosen here. However, when looking at this figure, we assume that all the other factors average out.

Due to the time-cost of the expression we found, it

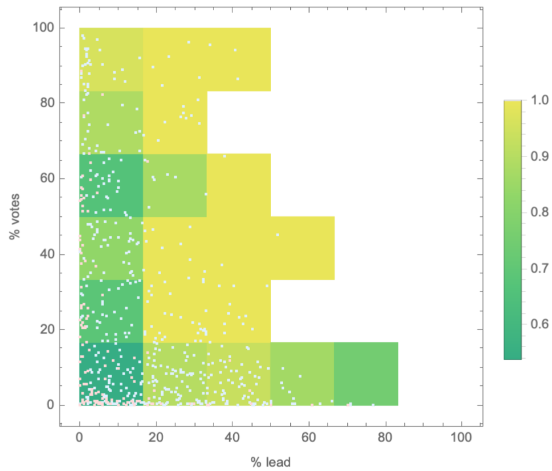

Figure 4: Plot of the collected data

is not really feasible to try and draw it continuously, especially when taking into account that we need to average it over all other factors, which would most likely involve even more integrals.

Therefore, we need to resort to an other method for visualizing it. The solution I found was to generate random points in the 6-dimensional space, feeding them through the function we built and finally graphing in them in the same way that we did for the real-world data in Figure 4. The only difference in the graph is that the bins would now be coloured based on the average of the points they were containing, as each point already represents the probability for a lead candidate to be elected.

However, we need to keep in mind that all the other factors should not necesseraly be uniformly random, but distributed in some way in order to make our random data set more similar to the real-world.

This is why the total number of votes was generated using the normal distribution found in Section 3 (mean of 43 476 and standard deviation of 13 106), truncated to a reasonnable range, 8000 to 80 000, in order to prevent ridiculously small or large values to come in and skew our graph. These bounds were chosen based on the constituencies with the most / the least votes.

The principal downside to using random points is that it allows for some random variation in the graphs, which is why the graphs below were made with as many points as possible.

Plotting the graph described above yields Figure 14.

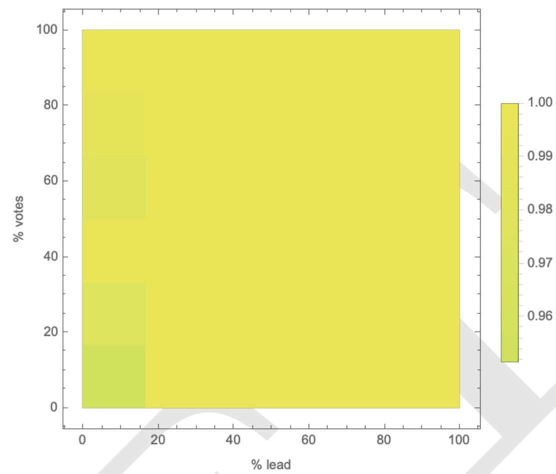

Figure 14: Plot of the model from Section 4.7

As we may notice, there is something horribly wrong here: the plot is completely yellow! If our model predicts a 0.95 probability of winning even when only 0 % to 16.67 % of votes were counted and the leading candidate only had 0 % to 16.67 % of lead, it means that it gets really quite convinced about future outcomes even after seeing only very little, very unconvincing, data. This means that each vote we feed the model carries too much certainty.

The simplest fix for this would therefore be to scale down the number of votes we give the model by a certain scaling constant, let's call it S, in order to diminish their importance. The rationale for this probably lies in the fact that we assumed each vote to be completely independent, even though this is probably not the case in real-life, where many factors influence the relation between different votes.

Examples of this may include: (I) opinions varying between different geographic parts of the constituency (II) herd mentality taking place (III) individuals trying to account for the failures of the first-past-the-post voting system (not voting for their favorite candidate in order to prevent a candidate they dislike getting into office), although this is probably more a humanities question than a mathematical one.

Applying this fix to our model is fortunately really quite trivial. In fact, we only need to divide each value of the set of votes per candidate v by the scaling constant S before calculating the total number of votes v_t, the number of expected votes v_e and the expected number of votes left to be counted v_l. After this is done, we can simply use the formula found in Section 4.7.

For example, using the example data from Section 4 and a scaling constant $S = 10$, we would get the following values.

$$
\begin{aligned}
n &= 5 \\
v &= \left\{ \frac{60}{10}, \frac{50}{10}, \frac{36}{10}, \frac{34}{10}, \frac{20}{10} \right\} \\
&= \{6, 5, 3.6, 3.4, 2, 1\} \\
v_t &= 6 + 5 + 3.6 + 3.4 + 2 = 20 \\
b_c &= 10 \\
b_t &= 16 \\
v_e &= \frac{16}{10}(200) = 32 \\
v_l &= 32 - 20 = 12
\end{aligned}
$$

This simply has the effect of scaling everyone of those calculated values by a factor of S, in this case 10. This means that we now consider the first candidate to have 6 votes, the second 5, the third 3.6, etc. Furthermore, the total number of votes v_t is now 20 instead of 200, the expected number of votes v_e is is 32 instead of 320 and the expected number of votes left v_l is 12 instead of 120.

As justified earlier in Section 4.7, it is perfectly valid to use non-integer values in our function, as it doesn't rely on any integer-only functions or operations.

With this scaling back of $S = 10$, we now would get the following probabilities as our predictions.

Table 2: Predictions from first, second and third model

Candidate #	Section 4.6	Section 4.7	Section 5
1	0.86658	0.96604	0.66200
2	0.13183	0.03395	0.25740
3	0.00012	0.00000	0.04492
4	0.00004	0.00000	0.03321
5	0.00000	0.00000	0.00246

As we can see, the model with the scaling down produces values that are much much closer to each other. The model got a lot calculated a much smaller probability for the first candidate to win and a much bigger one for all the others, just as we wanted.

An other nice benefit of scaling back the number of votes by a scaling factor is that this greatly decreases the time required to compute values with the model. It is hard to definitively conclude why this is the case without a depper look into the way the mathematics engine used (in my case, Wolfram Mathematica [30]) approximates integrals, but one could suppose that this is due to the values we are working with being much smaller as a result of the scaling down.

However, we now need to find an optimal value for S that maximizes the accuracy of our model[13]. First, we need to define a metric for how *good* a certain value of S is. I believe a sufficient way to evaluate this would be to generate a plot of the model for a certain value of S and look at the difference, for each bin, between the calculated probability of the leading candidate winning and the real-world probability from the equivalent bin. Then, we could take the average of these differences and use that as our metric for the value of S. Our goal would then be to find the value of S that minimizes this average error. This can be visualized in Figure 15.

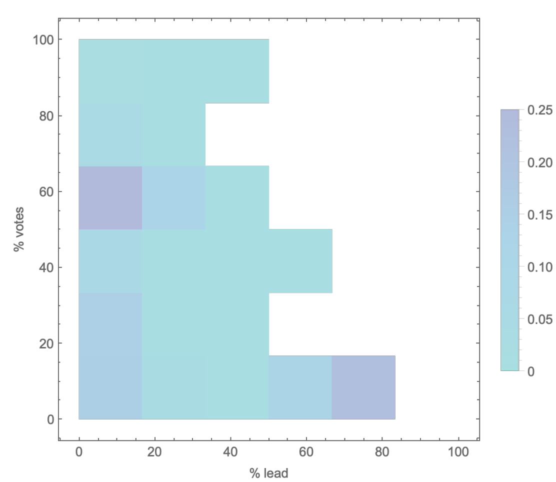

Figure 15: Plot of the error in the model for $S = 100$

[13]For the sake of brevity, the following steps will be a simple attempt at optimizing this parameter. However, a more rigorous and complete working of the optimal value would make a most interesting extension to this paper.

In Figure 15, we can see how the error varies bin per bin, from approximately 0 at 33.33 % to 50 % of lead and 83.33 % to 100 % of votes counted up to approximately 0.25 at 0 % to 16.67 % of lead and 50 % to 66.67 % of votes counted. Calculating the average of the different bins in this plot would yield an average error of approximately 0.0596.

However, it is important to realize that this graph is susceptible to quite a few sources of error[14]:

1. The real-world data does probably contain quite a few anomalies due to the relatively small dataset gathered (approximately 600 points divided in 36 bins only leaves about 16 points per bin, with some having much less).
2. This also means that changing the number of bins would probably change the average error in the plot due to point boundaries moving.
3. The model plot being generated from random points, it is also somewhat susceptible to random error.

For example, the bin at 0 % to 16.67 % of lead and 50 % to 66.67 % in the real world data-plot does seem to have an abnormally low probability of the leading candidate being elected compared to its neighbours, as can be seen in Figure 4.

Furthermore, many different error calculations could have been used. For example, as we only look at the average, we do not take into account the variation of the error. The one selected here gives an idea of when looking at a value from the model, what should we expect the error on the probability to be.

Calculating the average error for some values of S gives the following results[15]:

Table 3: Values of S tested with the number of random points used and the average error

Value of S	Number of random points	Average error
1	835	0.0999
3	2865	0.0972
100	5000	0.0596
251	5000	0.0449
376	5000	0.0498
500	5000	0.0495
544	5000	0.0542
587	5000	0.0550
1000	5000	0.0818

Those points where selected almost randomly within a reasonable range of values for S (1 to 1000), while approximately using an approximate binary-search inspired algorithm (starting at the extremes of the reasonable range values and recursively testing values in their middle). The point $S = 251$ was also selected, as it is approximately the average number of votes per ballot box in the collected dataset.

Out of these points, $S = 251$ seems to be the optimal value, having the smallest average error. This seems to indicate that even though individual votes are not truly independent, individual ballot boxes seem to be, as they give an outcome really quite close to the real-world data, with an average error of only approximately 0.0449. This version of the model and its error can be visualized in Figures 16 and 17.

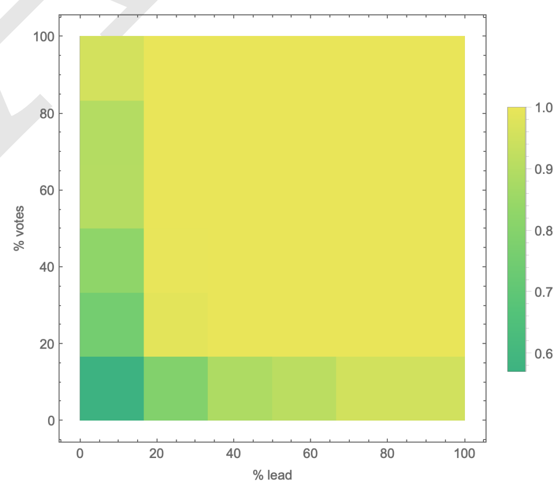

Figure 16: Plot of the model for $S = 251$

As we can see, the mathematical model with $S = 251$ produces an output (Figure 16) really quite similar to the real-world data (Figure 4), to the exceptions of some anomalies.

This is in terms shown in Figure 17 by a mostly blue graph, indicating a very small ber bin difference and, therefore, a very small average difference.

Figure 16 also shows the general trend we were

[14]Although a quantitative way to handle these error sources would be most helpful, such a thing has been deemed outside of the scope of the investigation.

[15]Smaller values of S have less random points, as they are much more expansive to calculate.

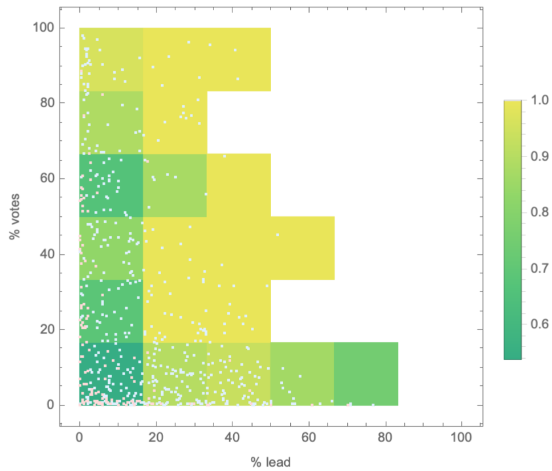

Figure 4: Plot of the collected data

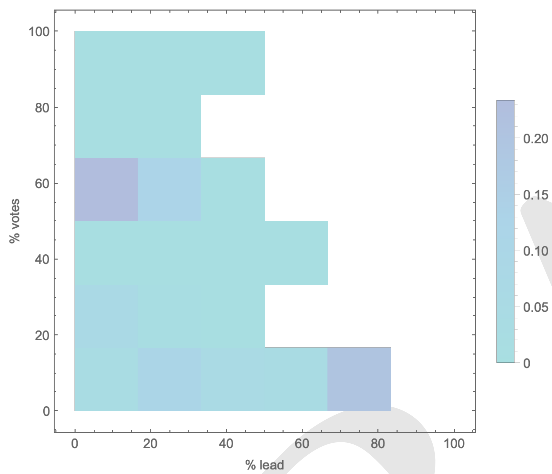

Figure 17: Plot of the error in the model for $S = 251$

expecting: the more votes are counted and the more lead the leading candidate has, the higher are his changes of winning. We can also observe other, more specific, trends, such as the fact that the probability of being elected gets really quite close to 1 as soon as more than approximately 16.67 % of votes are counted and that there is more than 16.67 % lead.

6. Conclusion

In conclusion, thanks to the tools of conditional probability, we were able to build a mathematical model to calculate the probability that a certain candidate in a constituency has to win. To do so, we first built a likelihood function to summarize the probability to observe the current evidence (the number of votes for each candidate) and then constructed our prior beliefs using prior elicitation to summarize what we thought about each candidate before watching the election, based on, for example, survey data. We were then able to combine those two pieces of information using Bayes' theorem to obtain a probability distribution representing the probability that a certain candidate had a certain probability to win the next vote. Using a translated beta-binomial distribution, we were then able to find the final expected number of votes per candidate, which we could then compare to find the probability that a certain candidate would win. Finally, we realized that we needed to scale back the number of votes we were feeding into the model in order to make its output be much closer to the real-world data we gathered in the beginning. The optimal value we found for the scaling factor 251, although the optimization techniques used here where less than optimal.

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Appendices

A. Collected Data

Constituency	Boxes Counted	Total Boxes	RDI Elected	First	First Count	Second	Second Count	Third	Third Count	Fourth	Fourth Count	Fifth	Fifth Count	Total Votes	End Winner	End Total Votes
ABITIBI BAIE JAMES NUNAVIK EEYOU	1	210	No	NDP	17	PPC	12	LPC	8	CPC	4	Other	0	41	BQ	28436
ABITIBI TEMISCAMINGUE	1	263	No	BQ	130	LPC	75	CPC	46	PPC	13	Other	0	264	BQ	45685
ACADIE BATHURST	1	218	No	LPC	34	NDP	10	PPC	6	CPC	3	Other	0	53	LPC	42922
ACADIE BATHURST	25	218	No	LPC	1429	CPC	429	NDP	290	PPC	208	Other	0	2356	LPC	42922
AHUNTSIC CARTIERVILLE	1	234	No	LPC	61	BQ	39	CPC	7	PPC	2	Other	0	109	LPC	50409
AHUNTSIC CARTIERVILLE	60	234	No	LPC	5357	BQ	2147	NDP	1384	CPC	861	Other	0	9749	LPC	50409
ALGOMA MANITOULIN KAPUSKASING	216	220	No	NDP	14216	CPC	10349	LPC	7901	PPC	2772	Other	0	35238	NDP	39523
ARGENTEUIL LA PETITE NATION	1	253	No	LPC	16	BQ	4	CPC	3	Other	2	Other	0	25	LPC	50613
ARGENTEUIL LA PETITE NATION	80	253	No	BQ	4514	LPC	4506	CPC	1585	NDP	843	Other	0	11448	LPC	50613
ARGENTEUIL LA PETITE NATION	250	253	No	LPC	18064	BQ	16975	CPC	6213	NDP	3253	Other	0	44505	LPC	50613
AVALON	1	233	No	LPC	20	CPC	15	NDP	2	PPC	1	Other	0	38	LPC	37144
AVALON	32	233	No	LPC	1714	CPC	1280	NDP	388	PPC	66	Other	0	3448	LPC	37144
AVALON	61	233	No	LPC	3507	CPC	2670	NDP	793	PPC	156	Other	0	7126	LPC	37144
AVIGNON LA MITIS MATANE MATAPEDIA	1	206	No	BQ	177	LPC	55	CPC	32	NDP	11	Other	0	275	BQ	33075
AVIGNON LA MITIS MATANE MATAPEDIA	193	206	No	BQ	18202	LPC	6361	CPC	2681	NDP	1428	Other	0	28672	BQ	33075
BEAUCE	1	272	No	LPC	3	CPC	1	BQ	1	PPC	1	Other	0	6	CPC	56980
BEAUCE	11	272	No	CPC	368	BQ	111	LPC	96	PPC	91	Other	0	666	CPC	56980
BEAUCE	35	272	No	CPC	2545	PPC	977	BQ	738	LPC	715	Other	0	4975	CPC	56980
BEAUPORT COTE DE BEAUPRE ILE D'ORLEANS CHARLEVOIX	139	221	No	BQ	10946	CPC	7637	LPC	5387	NDP	1043	Other	0	25013	BQ	50136
BEAUPORT LIMOILOU	5	208	No	LPC	238	CPC	152	BQ	145	NDP	18	Other	0	553	BQ	48644
BEAUPORT LIMOILOU	10	208	No	LPC	438	CPC	400	BQ	355	NDP	86	Other	0	1279	BQ	48644
BEAUPORT LIMOILOU	62	208	No	CPC	2625	BQ	2616	LPC	2553	NDP	1055	Other	0	8849	BQ	48644
BEAUPORT LIMOILOU	70	208	No	CPC	3103	BQ	3070	LPC	2873	NDP	1210	Other	0	10256	BQ	48644
BEAUPORT LIMOILOU	73	208	No	CPC	3283	BQ	3214	LPC	2968	NDP	1239	Other	0	10704	BQ	48644
BEAUPORT LIMOILOU	85	208	No	CPC	3866	BQ	3841	LPC	3420	NDP	1455	Other	0	12582	BQ	48644
BEAUPORT LIMOILOU	107	208	No	CPC	4648	BQ	4609	LPC	4187	NDP	1702	Other	0	15146	BQ	48644
BEAUSEJOUR	1	202	No	LPC	64	CPC	25	PPC	20	NDP	14	Other	0	123	LPC	49145
BEAUSEJOUR	25	202	No	LPC	2036	CPC	620	NDP	385	PPC	316	Other	0	3357	LPC	49145
BECANCOUR NICOLET SAUREL	3	243	No	BQ	87	LPC	71	Other	10	CPC	7	Other	0	175	BQ	50007
BECANCOUR NICOLET SAUREL	25	243	No	BQ	1676	LPC	524	CPC	342	NDP	133	Other	0	2675	BQ	50007
BECANCOUR NICOLET SAUREL	100	243	No	BQ	7727	LPC	2471	CPC	2361	NDP	827	Other	0	13386	BQ	50007
BELLECHASSE LES ETCHEMINS LEVIS	160	326	No	CPC	11276	BQ	4627	LPC	3500	NDP	1171	Other	0	20574	CPC	63182
BELOEIL CHAMBLY	1	292	No	BQ	383	LPC	144	CPC	49	NDP	44	Other	0	620	BQ	65324
BELOEIL CHAMBLY	5	292	No	BQ	1536	LPC	577	CPC	227	NDP	206	Other	0	2546	BQ	65324
BELOEIL CHAMBLY	36	292	No	BQ	5131	LPC	2166	CPC	826	NDP	703	Other	0	8826	BQ	65324
BERTHIER MASKINONGE	1	274	No	NDP	6	BQ	4	LPC	3	CPC	1	Other	0	14	BQ	54945
BERTHIER MASKINONGE	67	274	No	NDP	3120	BQ	2537	LPC	1186	CPC	1086	Other	0	7929	BQ	54945
BERTHIER MASKINONGE	130	274	No	NDP	6297	BQ	5344	LPC	2457	CPC	2037	Other	0	16135	BQ	54945
BERTHIER MASKINONGE	160	274	No	NDP	7733	BQ	6886	LPC	3055	CPC	2504	Other	0	20178	BQ	54945
BERTHIER MASKINONGE	215	274	No	NDP	10517	BQ	9936	LPC	4373	CPC	3383	Other	0	28209	BQ	54945
BERTHIER MASKINONGE	265	274	No	BQ	16736	NDP	16131	LPC	7778	CPC	5167	Other	0	45812	BQ	54945
BERTHIER MASKINONGE	266	274	No	BQ	17275	NDP	16349	LPC	7934	CPC	5264	Other	0	46822	BQ	54945
BONAVISTA BURIN TRINITY	1	275	No	LPC	8	CPC	3	NDP	0	PPC	0	Other	0	11	LPC	29991
BONAVISTA BURIN TRINITY	2	275	No	CPC	50	LPC	39	NDP	5	PPC	1	Other	0	95	LPC	29991
BONAVISTA BURIN TRINITY	15	275	No	CPC	467	LPC	437	NDP	51	PPC	51	Other	0	1006	LPC	29991
BONAVISTA BURIN TRINITY	35	275	No	LPC	1219	CPC	1135	NDP	173	PPC	117	Other	0	2644	LPC	29991
BONAVISTA BURIN TRINITY	55	275	No	CPC	2166	LPC	2139	NDP	314	PPC	198	Other	0	4817	LPC	29991
BONAVISTA BURIN TRINITY	200	275	No	LPC	9467	CPC	8189	NDP	1591	PPC	845	Other	0	20092	LPC	29991
BOURASSA	36	198	No	LPC	2376	BQ	619	NDP	304	CPC	255	Other	0	3554	LPC	36932
BROME MISSISQUOI	195	279	No	BQ	9655	LPC	9449	CPC	4708	NDP	2170	Other	0	25982	LPC	61471
BROME MISSISQUOI	230	279	No	BQ	11797	LPC	11608	CPC	5622	NDP	2648	Other	0	31675	LPC	61471
BROSSARD SAINT LAMBERT	53	234	No	LPC	4001	BQ	1318	CPC	748	NDP	739	Other	0	6806	LPC	52356
BURNABY SOUTH	27	191	No	NDP	1056	LPC	921	CPC	739	PPC	101	Other	0	2817	NDP	40608
BURNABY SOUTH	35	191	No	NDP	1420	LPC	1228	CPC	1002	PPC	129	Other	0	3779	NDP	40608
BURNABY SOUTH	147	191	No	NDP	10276	LPC	8083	CPC	5926	PPC	902	Other	0	25187	NDP	40608
CAPE BRETON CANSO	1	214	No	LPC	34	CPC	34	NDP	26	PPC	1	Other	0	95	LPC	39360
CAPE BRETON CANSO	95	214	No	LPC	6331	CPC	4527	NDP	2294	PPC	611	Other	0	13763	LPC	39360
CARDIGAN	18	95	No	LPC	2069	CPC	1238	NDP	362	GPC	184	Other	0	3853	LPC	22094
CENTRAL NOVA	70	232	No	LPC	3312	CPC	2441	NDP	1205	PPC	295	Other	0	7253	LPC	40474
CHARLESBOURG HAUTE SAINT CHARLES	145	242	No	CPC	8830	BQ	5382	LPC	4577	NDP	1684	Other	0	20473	CPC	57349
CHATEAUGUAY LACOLLE	2	222	No	BQ	164	LPC	159	CPC	81	PPC	23	Other	0	427	LPC	48683
CHATEAUGUAY LACOLLE	18	222	No	BQ	1624	LPC	1145	CPC	558	NDP	190	Other	0	3517	LPC	48683
CHATEAUGUAY LACOLLE	29	222	No	BQ	3246	LPC	2048	CPC	1053	NDP	378	Other	0	6725	LPC	48683
CHATEAUGUAY LACOLLE	155	222	No	BQ	12852	LPC	11926	CPC	4043	NDP	2510	Other	0	31331	LPC	48683
CHICOUTIMI LE FJORD	4	161	No	BQ	95	LPC	77	CPC	63	NDP	15	Other	0	250	CPC	42006
CHICOUTIMI LE FJORD	100	161	No	CPC	7139	BQ	6151	LPC	3371	NDP	1030	Other	0	17691	CPC	42006
CHICOUTIMI LE FJORD	120	161	No	CPC	9586	BQ	7966	LPC	4324	NDP	1327	Other	0	23203	CPC	42006
CHURCHILL KEEWATINOOK ASKI	115	157	No	NDP	5025	LPC	3021	CPC	3014	PPC	631	Other	0	11691	NDP	17927
COAST OF BAYS CENTRAL NOTRE DAME	1	246	No	LPC	23	CPC	4	NDP	0	Other	0	Other	0	27	CPC	31834
COAST OF BAYS CENTRAL NOTRE DAME	45	246	No	LPC	1397	CPC	1331	NDP	192	Other	0	Other	0	2920	CPC	31834
COAST OF BAYS CENTRAL NOTRE DAME	80	246	No	LPC	3050	CPC	2961	NDP	482	Other	0	Other	0	6493	CPC	31834
COAST OF BAYS CENTRAL NOTRE DAME	120	246	No	CPC	5161	LPC	4915	NDP	788	Other	0	Other	0	10864	CPC	31834
COAST OF BAYS CENTRAL NOTRE DAME	159	246	No	CPC	7260	LPC	6849	NDP	1120	Other	0	Other	0	15229	CPC	31834

Constituency	Boxes Counted	Total Boxes	RDI Elected	First	First Count	Second	Second Count	Third	Third Count	Fourth	Fourth Count	Fifth	Fifth Count	Total Votes	End Winner	End Total Votes
COAST OF BAYS CENTRAL NOTRE DAME	243	246	No	CPC	13874	LPC	13125	NDP	2140	Other	0	Other	0	29139	CPC	31834
COMPTON STANSTEAD	220	275	No	LPC	13308	BQ	11229	CPC	6511	NDP	2848	Other	0	33896	LPC	57796
CUMBERLAND COLCHESTER	15	218	No	CPC	742	LPC	618	NDP	200	PPC	89	Other	0	1649	CPC	40417
CUMBERLAND COLCHESTER	34	218	No	CPC	1578	LPC	1188	NDP	447	PPC	164	Other	0	3377	CPC	40417
CUMBERLAND COLCHESTER	108	218	No	CPC	6310	LPC	4637	NDP	1771	PPC	631	Other	0	13349	CPC	40417
DARTMOUTH COLE HARBOUR	1	209	No	NDP	232	LPC	223	PPC	65	GPC	26	Other	0	546	LPC	45628
DARTMOUTH COLE HARBOUR	15	209	No	LPC	1229	NDP	1002	PPC	308	GPC	77	Other	0	2616	LPC	45628
DORVAL LACHINE LASALLE	69	233	No	LPC	5727	BQ	1745	NDP	1633	CPC	1352	Other	0	10457	LPC	48141
DURHAM	1	217	No	CPC	29	LPC	15	NDP	4	PPC	0	Other	0	48	CPC	67730
DURHAM	34	217	No	CPC	2874	LPC	1485	NDP	1010	PPC	313	Other	0	5682	CPC	67730
EDMONTON CENTRE	3	209	No	LPC	75	CPC	71	NDP	37	PPC	4	Other	0	187	LPC	49148
EDMONTON STRATHCONA	150	216	No	NDP	17570	CPC	7847	LPC	2304	PPC	1558	Other	0	29279	NDP	52223
EGMONT	51	100	No	LPC	3010	CPC	2074	GPC	699	NDP	620	Other	0	6403	LPC	19561
ELMWOOD TRANSCONA	175	188	No	NDP	15839	CPC	8856	LPC	4795	PPC	1881	Other	0	31371	NDP	41839
FREDERICTON	1	154	No	LPC	3	CPC	2	GPC	2	NDP	0	Other	0	7	LPC	44062
FREDERICTON	6	154	No	CPC	784	LPC	466	GPC	205	NDP	182	Other	0	1637	LPC	44062
FREDERICTON	29	154	No	CPC	2007	LPC	1971	GPC	847	NDP	779	Other	0	5604	LPC	44062
FREDERICTON	63	154	No	CPC	4235	LPC	4101	NDP	1750	GPC	1699	Other	0	11785	LPC	44062
FREDERICTON	80	154	No	LPC	6272	CPC	6109	NDP	2395	GPC	2354	Other	0	17130	LPC	44062
FREDERICTON	85	154	No	CPC	6590	LPC	6575	NDP	2599	GPC	2455	Other	0	18219	LPC	44062
FREDERICTON	104	154	No	CPC	8484	LPC	8357	NDP	3330	GPC	3116	Other	0	23287	LPC	44062
FREDERICTON	148	154	No	LPC	14834	CPC	14524	NDP	5207	GPC	5167	Other	0	39732	LPC	44062
FUNDY ROYAL	1	200	No	LPC	3	NDP	3	CPC	1	PPC	1	Other	0	8	CPC	44382
FUNDY ROYAL	30	200	No	CPC	1950	LPC	948	NDP	601	PPC	490	Other	0	3989	CPC	44382
GASPESIE LES ILES DE LA MADELEINE	1	223	No	BQ	115	LPC	84	CPC	43	NDP	5	Other	0	247	LPC	36858
GASPESIE LES ILES DE LA MADELEINE	4	223	No	BQ	212	LPC	208	CPC	70	NDP	40	Other	0	530	LPC	36858
GASPESIE LES ILES DE LA MADELEINE	8	223	No	LPC	340	BQ	326	CPC	106	NDP	53	Other	0	825	LPC	36858
GASPESIE LES ILES DE LA MADELEINE	10	223	No	BQ	444	LPC	413	CPC	143	NDP	59	Other	0	1059	LPC	36858
GASPESIE LES ILES DE LA MADELEINE	15	223	No	LPC	833	BQ	706	CPC	206	NDP	97	Other	0	1842	LPC	36858
GASPESIE LES ILES DE LA MADELEINE	40	223	No	LPC	2276	BQ	1772	CPC	411	NDP	235	Other	0	4694	LPC	36858
GASPESIE LES ILES DE LA MADELEINE	55	223	No	LPC	3089	BQ	2478	CPC	534	NDP	293	Other	0	6394	LPC	36858
GATINEAU	1	223	No	GPC	54	Other	16	CPC	4	PPC	2	Other	0	76	LPC	52497
GATINEAU	65	223	No	LPC	6249	BQ	2847	CPC	1344	NDP	1052	Other	0	11492	LPC	52497
HALIFAX	1	184	No	LPC	14	CPC	6	NDP	3	GPC	1	Other	0	24	LPC	51248
HAMILTON CENTRE	130	194	No	NDP	12651	LPC	6821	CPC	4010	PPC	1719	Other	0	25201	NDP	41280
HONORE MERCIER	1	219	No	LPC	63	BQ	14	CPC	12	NDP	11	Other	0	100	LPC	48409
HONORE MERCIER	3	219	No	LPC	88	BQ	25	CPC	13	NDP	13	Other	0	139	LPC	48409
HONORE MERCIER	60	219	No	LPC	7183	BQ	2180	CPC	1274	NDP	835	Other	0	11472	LPC	48409
HULL AYLMER	31	213	No	LPC	2656	BQ	743	NDP	739	CPC	541	Other	0	4679	LPC	51249
JOLIETTE	10	272	No	LPC	512	BQ	339	CPC	88	Other	17	Other	0	956	BQ	56198
JOLIETTE	45	272	No	BQ	5457	LPC	2586	CPC	965	NDP	518	Other	0	9526	BQ	56198
JONQUIERE	190	223	No	BQ	16538	CPC	11894	LPC	8272	NDP	2430	Other	0	39134	BQ	45474
KENORA	12	150	No	NDP	623	LPC	177	CPC	171	PPC	27	Other	0	998	CPC	26083
KINGS HANTS	2	228	No	LPC	110	CPC	91	NDP	57	GPC	10	Other	0	268	LPC	44956
KITCHENER CENTRE	3	216	No	GPC	289	NDP	179	LPC	157	CPC	157	Other	0	782	GPC	51179
KITCHENER CENTRE	145	216	No	GPC	7426	CPC	5811	NDP	4309	LPC	4128	Other	0	21674	GPC	51179
LA POINTE DE L'ILE	182	262	No	BQ	12267	LPC	9160	NDP	2729	CPC	1893	Other	0	26049	BQ	51080
LABRADOR	1	88	No	LPC	24	NDP	6	CPC	5	PPC	1	Other	0	36	LPC	9653
LABRADOR	45	88	No	LPC	1851	CPC	1231	NDP	939	PPC	117	Other	0	4138	LPC	9653
LAC SAINT JEAN	1	304	No	BQ	43	LPC	32	CPC	7	NDP	0	Other	0	82	BQ	50197
LAC SAINT JEAN	50	304	No	BQ	2369	CPC	1219	LPC	991	NDP	168	Other	0	4747	BQ	50197
LAC SAINT LOUIS	44	233	No	LPC	3902	CPC	1380	NDP	1122	BQ	428	Other	0	6832	LPC	57725
LASALLE EMARD VERDUN	85	209	No	LPC	6651	BQ	3334	NDP	2795	CPC	1217	Other	0	13997	LPC	47360
LAURENTIDES LABELLE	5	296	No	BQ	1240	LPC	679	CPC	278	NDP	135	Other	0	2332	BQ	64123
LAURENTIDES LABELLE	267	296	No	BQ	27135	LPC	13569	CPC	5716	NDP	3259	Other	0	49679	BQ	64123
LAURIER SAINTE MARIE	35	178	No	LPC	2293	NDP	1935	BQ	1178	CPC	225	Other	0	5631	LPC	44676
LAURIER SAINTE MARIE	43	178	No	LPC	2779	NDP	2515	BQ	1488	CPC	271	Other	0	7053	LPC	44676
LAVAL LES ILES	2	222	No	LPC	54	BQ	34	CPC	14	PPC	3	Other	0	105	LPC	50597
LEVIS LOTBINIERE	240	298	No	CPC	25708	BQ	10899	LPC	7268	NDP	3529	Other	0	47404	CPC	63407
LONDON FANSHAWE	200	240	No	NDP	13374	LPC	7412	CPC	7266	PPC	2786	Other	0	30838	NDP	51422
LONG RANGE MOUNTAINS	1	265	No	CPC	55	LPC	29	PPC	2	NDP	1	Other	0	87	LPC	36447
LONG RANGE MOUNTAINS	4	265	No	CPC	149	LPC	111	NDP	8	PPC	8	Other	0	276	LPC	36447
LONG RANGE MOUNTAINS	10	265	No	LPC	252	CPC	241	NDP	41	PPC	25	Other	0	559	LPC	36447
LONG RANGE MOUNTAINS	80	265	No	LPC	3354	CPC	3231	NDP	676	PPC	365	Other	0	7626	LPC	36447
LONG RANGE MOUNTAINS	210	265	No	LPC	11090	CPC	9929	NDP	2875	PPC	1195	Other	0	25089	LPC	36447
LONGUEUIL CHARLES LEMOYNE	165	230	No	LPC	8825	BQ	7425	NDP	2854	CPC	1913	Other	0	21017	LPC	47970
LONGUEUIL SAINT HUBERT	3	233	No	LPC	136	BQ	120	NDP	22	CPC	10	Other	0	288	BQ	57235
LONGUEUIL SAINT HUBERT	25	233	No	LPC	1653	BQ	1646	NDP	358	CPC	264	Other	0	3921	BQ	57235
LONGUEUIL SAINT HUBERT	42	233	No	LPC	2747	BQ	2743	NDP	623	CPC	450	Other	0	6563	BQ	57235
LONGUEUIL SAINT HUBERT	87	233	No	LPC	5749	BQ	5465	NDP	1325	CPC	956	Other	0	13495	BQ	57235
LONGUEUIL SAINT HUBERT	95	233	No	LPC	6245	BQ	5924	NDP	1439	CPC	1050	Other	0	14658	BQ	57235
LONGUEUIL SAINT HUBERT	185	233	No	LPC	13253	BQ	12901	NDP	3065	CPC	2317	Other	0	31536	BQ	57235
LOUIS SAINT LAURENT	136	255	No	CPC	12121	BQ	4709	LPC	4290	NDP	1563	Other	0	22683	CPC	64098
MADAWASKA RESTIGOUCHE	40	144	No	LPC	2479	CPC	1343	NDP	462	PPC	393	Other	0	4677	LPC	30546
MALPEQUE	1	90	No	LPC	313	CPC	209	GPC	81	NDP	47	Other	0	650	LPC	23707
MANICOUAGAN	245	261	No	BQ	15127	CPC	6332	LPC	5563	NDP	1379	Other	0	28401	BQ	35000
MEGANTIC L'ERABLE	2	243	No	CPC	874	BQ	319	LPC	245	PPC	25	Other	0	1463	CPC	46428
MEGANTIC L'ERABLE	30	243	No	CPC	5294	BQ	1953	LPC	1353	PPC	206	Other	0	8806	CPC	46428
MIRABEL	120	268	No	BQ	10081	LPC	5497	CPC	2856	NDP	2239	Other	0	20673	BQ	63112
MIRAMICHI GRAND LAKE	3	158	No	LPC	206	CPC	168	NDP	53	PPC	28	Other	0	455	CPC	32503
MIRAMICHI GRAND LAKE	25	158	No	CPC	1611	LPC	1439	NDP	365	PPC	286	Other	0	3701	CPC	32503
MONCTON RIVERVIEW DIEPPE	25	187	No	LPC	2790	CPC	1304	NDP	914	PPC	329	Other	0	5337	LPC	45762
MONTARVILLE	1	216	No	LPC	82	BQ	72	NDP	40	CPC	13	Other	0	207	BQ	57472
MONTARVILLE	20	216	No	LPC	1226	BQ	1196	NDP	393	CPC	292	Other	0	3107	BQ	57472
MONTARVILLE	74	216	No	BQ	5368	LPC	4781	NDP	1453	CPC	1251	Other	0	12853	BQ	57472
MONTARVILLE	165	216	No	BQ	15186	LPC	12560	CPC	3281	NDP	3276	Other	0	34303	BQ	57472
MONTCALM	178	236	No	BQ	20198	LPC	7308	CPC	4291	NDP	2284	Other	0	34081	BQ	51452
MONTMAGNY L'ISLET KAMOURASKA RIVIERE DU LOUP	1	271	No	LPC	7	CPC	7	BQ	2	NDP	0	Other	0	16	CPC	47812
MONTMAGNY L'ISLET KAMOURASKA RIVIERE DU LOUP	10	271	No	CPC	377	LPC	188	BQ	142	Other	27	Other	0	734	CPC	47812
MONTMAGNY L'ISLET KAMOURASKA RIVIERE DU LOUP	108	271	No	CPC	8775	BQ	4140	LPC	2786	NDP	507	Other	0	16208	CPC	47812
NEW BRUNSWICK SOUTHWEST	30	176	No	CPC	2211	LPC	885	NDP	587	PPC	437	Other	0	4120	CPC	36629
NOTRE DAME DE GRACE WESTMOUNT	32	214	No	LPC	2439	NDP	800	CPC	675	GPC	214	Other	0	4128	LPC	45591

Constituency	Boxes Counted	Total Boxes	RDI Elected	First	First Count	Second	Second Count	Third	Third Count	Fourth	Fourth Count	Fifth	Fifth Count	Total Votes	End Winner	End Total Votes
ORLEANS	30	238	No	LPC	2718	CPC	1667	NDP	944	PPC	174	Other	0	5503	LPC	75283
PAPINEAU	18	212	No	LPC	115	NDP	47	BQ	26	CPC	11	Other	0	199	LPC	45423
PAPINEAU	28	212	No	LPC	910	NDP	427	BQ	234	CPC	106	Other	0	1677	LPC	45423
PIERRE BOUCHER LES PATRIOTES VERCHERES	175	239	No	BQ	14367	LPC	6808	NDP	2493	CPC	2445	Other	0	26113	BQ	55246
QUEBEC	30	241	No	LPC	1356	BQ	1045	CPC	825	NDP	709	Other	0	3935	LPC	51191
REPENTIGNY	185	270	No	BQ	19380	LPC	10354	CPC	3357	NDP	3118	Other	0	36209	BQ	59701
RICHMOND ARTHABASKA	170	279	No	CPC	12974	BQ	6465	LPC	3657	NDP	1401	Other	0	24497	CPC	57159
RIMOUSKI NEIGETTE TEMISCOUATA LES BASQUES	184	249	No	BQ	17148	LPC	8255	CPC	4423	NDP	2297	Other	0	32123	BQ	42138
RIVIERE DES MILLE ILES	196	235	No	BQ	11382	LPC	10246	CPC	3060	NDP	2623	Other	0	27311	BQ	53366
RIVIERE DU NORD	35	243	No	BQ	2216	LPC	926	CPC	549	NDP	375	Other	0	4066	BQ	57329
ROSEMONT LA PETITE PATRIE	1	234	No	NDP	178	LPC	140	BQ	128	CPC	12	Other	0	458	NDP	54988
ROSEMONT LA PETITE PATRIE	35	234	No	NDP	2778	LPC	1550	BQ	1194	CPC	235	Other	0	5757	NDP	54988
ROSEMONT LA PETITE PATRIE	218	234	No	NDP	21144	LPC	10105	BQ	8973	CPC	1801	Other	0	42023	NDP	54988
SAANICH GULF ISLANDS	1	236	No	GPC	524	CPC	271	NDP	214	LPC	196	Other	0	1205	GPC	65522
SAANICH GULF ISLANDS	75	236	No	GPC	4457	CPC	2309	NDP	2259	LPC	1984	Other	0	11009	GPC	65522
SACKVILLE PRESTON CHEZZETCOOK	1	198	No	LPC	15	CPC	10	NDP	7	PPC	5	Other	0	37	LPC	45606
SACKVILLE PRESTON CHEZZETCOOK	135	198	No	LPC	8143	NDP	6121	CPC	5213	PPC	904	Other	0	20381	LPC	45606
SAINT HYACINTHE BAGOT	213	256	No	BQ	21200	LPC	9795	CPC	6038	NDP	5104	Other	0	42137	BQ	53031
SAINT JEAN	221	258	No	BQ	14834	LPC	9166	CPC	4129	NDP	3014	Other	0	31143	BQ	59210
SAINT JOHN ROTHESAY	1	163	No	LPC	124	CPC	80	NDP	33	GPC	5	Other	0	242	LPC	37450
SAINT LEONARD SAINT MICHEL	1	201	No	LPC	312	BQ	40	NDP	35	CPC	24	Other	0	411	LPC	41814
SAINT MAURICE CHAMPLAIN	1	291	No	LPC	86	BQ	20	CPC	8	NDP	3	Other	0	117	LPC	56337
SAINT MAURICE CHAMPLAIN	2	291	No	LPC	107	BQ	41	CPC	20	NDP	4	Other	0	172	LPC	56337
SALABERRY SUROIT	266	302	No	BQ	26010	LPC	14805	CPC	6779	NDP	3999	Other	0	51593	BQ	60865
SHEFFORD	2	296	No	BQ	122	LPC	95	CPC	33	NDP	32	Other	0	282	BQ	59626
SHEFFORD	205	296	No	BQ	16151	LPC	12574	CPC	4648	NDP	2160	Other	0	35533	BQ	59626
SHERBROOKE	1	251	No	LPC	36	BQ	19	CPC	8	NDP	3	Other	0	66	LPC	58185
SHERBROOKE	75	251	No	LPC	3377	BQ	2488	NDP	1485	CPC	1151	Other	0	8501	LPC	58185
SOUTH SHORE ST. MARGARETS	5	270	No	LPC	223	CPC	201	NDP	135	GPC	19	Other	0	578	CPC	50004
SOUTH SHORE ST. MARGARETS	20	270	No	CPC	999	LPC	826	NDP	473	GPC	84	Other	0	2382	CPC	50004
SOUTH SHORE ST. MARGARETS	25	270	No	CPC	1222	LPC	994	NDP	594	GPC	107	Other	0	2917	CPC	50004
SOUTH SHORE ST. MARGARETS	40	270	No	CPC	2130	LPC	1651	NDP	934	GPC	174	Other	0	4889	CPC	50004
SOUTH SHORE ST. MARGARETS	165	270	No	CPC	9702	LPC	7926	NDP	4588	GPC	71	Other	0	22287	CPC	50004
ST. JOHN'S EAST	1	182	No	LPC	131	NDP	122	CPC	78	PPC	2	Other	0	333	LPC	38171
ST. JOHN'S EAST	2	182	No	NDP	165	LPC	147	CPC	92	PPC	8	Other	0	412	LPC	38171
ST. JOHN'S EAST	5	182	No	NDP	317	LPC	236	CPC	135	PPC	17	Other	0	705	LPC	38171
ST. JOHN'S EAST	10	182	No	NDP	522	LPC	455	CPC	325	PPC	39	Other	0	1341	LPC	38171
ST. JOHN'S EAST	20	182	No	NDP	1131	LPC	958	CPC	536	PPC	59	Other	0	2684	LPC	38171
ST. JOHN'S EAST	40	182	No	NDP	2255	LPC	2119	CPC	1133	PPC	137	Other	0	5644	LPC	38171
ST. JOHN'S EAST	65	182	No	LPC	3854	NDP	3514	CPC	1860	PPC	211	Other	0	9439	LPC	38171
ST. JOHN'S EAST	115	182	No	LPC	7052	NDP	6385	CPC	3476	PPC	383	Other	0	17296	LPC	38171
ST. JOHN'S EAST	160	182	No	LPC	10728	NDP	9134	CPC	5205	PPC	574	Other	0	25641	LPC	38171
ST. JOHN'S EAST	175	182	No	LPC	14411	NDP	11469	CPC	6453	PPC	671	Other	0	33004	LPC	38171
ST. JOHN'S SOUTH MOUNT PEARL	1	207	No	LPC	2	CPC	2	NDP	2	PPC	0	Other	0	6	LPC	34676
ST. JOHN'S SOUTH MOUNT PEARL	25	207	No	LPC	1541	NDP	742	CPC	486	PPC	64	Other	0	2833	LPC	34676
SYDNEY VICTORIA	1	205	No	CPC	99	LPC	31	NDP	16	PPC	6	Other	0	152	LPC	36312
SYDNEY VICTORIA	30	205	No	CPC	1618	LPC	1611	NDP	721	PPC	158	Other	0	4108	LPC	36312
SYDNEY VICTORIA	116	205	No	LPC	6364	CPC	5815	NDP	3370	PPC	554	Other	0	16103	LPC	36312
TERREBONNE	153	207	No	BQ	12700	LPC	10024	CPC	3250	NDP	2485	Other	0	28459	BQ	58949
TIMMINS JAMES BAY	148	176	No	NDP	9030	CPC	7183	LPC	5955	PPC	3578	Other	0	25746	NDP	34570
TOBIQUE MACTAQUAC	20	178	No	CPC	2278	LPC	945	NDP	367	PPC	258	Other	0	3848	CPC	34400
TORONTO CENTRE	5	137	No	LPC	742	NDP	289	CPC	216	GPC	116	Other	0	1363	LPC	45817
TORONTO CENTRE	15	137	No	LPC	1946	NDP	849	CPC	633	GPC	318	Other	0	3746	LPC	45817
TORONTO CENTRE	28	137	No	LPC	3293	NDP	1538	CPC	1006	GPC	543	Other	0	6380	LPC	45817
TORONTO CENTRE	50	137	No	LPC	5468	NDP	2669	CPC	1546	GPC	949	Other	0	10632	LPC	45817
TROIS RIVIERES	5	245	No	LPC	247	BQ	184	CPC	159	NDP	58	Other	0	648	BQ	58110
TROIS RIVIERES	40	245	No	LPC	1555	CPC	1488	BQ	1443	NDP	508	Other	0	4994	BQ	58110
TROIS RIVIERES	90	245	No	CPC	3615	BQ	3520	LPC	3472	NDP	1378	Other	0	11985	BQ	58110
TROIS RIVIERES	155	245	No	CPC	6646	BQ	6591	LPC	6210	NDP	2472	Other	0	21919	BQ	58110
TROIS RIVIERES	165	245	No	CPC	7131	BQ	7047	LPC	6661	NDP	2677	Other	0	23516	BQ	58110
TROIS RIVIERES	180	245	No	CPC	7610	BQ	7606	LPC	7326	NDP	2874	Other	0	25416	BQ	58110
TROIS RIVIERES	188	245	No	CPC	7782	BQ	7762	LPC	7574	NDP	2924	Other	0	26042	BQ	58110
TROIS RIVIERES	213	245	No	CPC	10196	BQ	10112	LPC	9879	NDP	3420	Other	0	33607	BQ	58110
VAUDREUIL SOULANGES	1	264	No	LPC	51	CPC	7	NDP	3	BQ	1	Other	0	62	LPC	64564
VILLE MARIE LE SUD OUEST ILE DES SOEURS	120	220	No	LPC	8694	NDP	3368	CPC	2193	BQ	2190	Other	0	16445	LPC	49423
WEST NOVA	5	244	No	CPC	443	LPC	137	NDP	98	PPC	39	Other	0	717	CPC	43871
WEST NOVA	49	244	No	CPC	3884	LPC	1883	NDP	867	PPC	426	Other	0	7060	CPC	43871
WINDSOR WEST	190	236	No	NDP	14400	LPC	9269	CPC	6525	PPC	2696	Other	0	32890	NDP	48693
WINNIPEG CENTRE	161	182	No	NDP	9045	LPC	5606	CPC	2487	PPC	826	Other	0	17964	NDP	29749
BARRIE SPRINGWATER ORO MEDONTE	21	67	No	LIB	6575	PCP	6370	NPD	1251	GPO	623	Other	0	14819	PCP	38862
BARRIE SPRINGWATER ORO MEDONTE	65	67	No	PCP	15950	LIB	15368	NPD	2960	GPO	1637	Other	0	35915	PCP	38862
BEACHES EAST YORK	22	41	No	LIB	6871	NPD	6472	PCP	3991	GPO	1939	Other	0	19273	LIB	40029
DUFFERIN CALEDON	4	61	No	PCP	986	GPO	471	LIB	306	NPD	252	Other	0	2015	PCP	45354
ESSEX	16	58	No	PCP	7234	NPD	4656	LIB	1254	Other	1243	Other	0	14387	PCP	47520
ETOBICOKE NORD	3	38	No	PCP	678	LIB	329	NPD	191	Other	38	Other	0	1236	PCP	24580
ETOBICOKE NORD	6	38	No	PCP	2409	LIB	1068	NPD	613	GPO	132	Other	0	4222	PCP	24580
GLENGARRY PRESCOTT RUSSELL	8	99	No	PCP	3420	LIB	2861	NPD	768	Other	452	Other	0	7501	PCP	43573
GLENGARRY PRESCOTT RUSSELL	12	99	No	PCP	4671	LIB	3954	NPD	1028	Other	587	Other	0	10240	PCP	43573
GLENGARRY PRESCOTT RUSSELL	82	99	No	PCP	13003	LIB	11258	NPD	2447	Other	1392	Other	0	28100	PCP	43573
GUELPH	1	86	No	GPO	400	PCP	97	LIB	62	NPD	47	Other	0	606	GPO	54185
GUELPH	9	86	No	GPO	3635	PCP	1270	LIB	801	NPD	540	Other	0	6246	GPO	54185
HALDIMAND NORFOLK	54	62	No	Other	14124	PCP	12047	NPD	5427	LIB	2772	Other	0	34370	IND	41765
HAMILTON CENTRE	6	53	No	NPD	1994	PCP	671	LIB	430	GPO	276	Other	0	3371	NDP	28326
HURON BRUCE	13	87	No	PCP	1090	NPD	414	LIB	348	Other	166	Other	0	2018	PCP	46129
KANATA CARLETON	15	54	No	PCP	5459	NPD	3271	LIB	2927	GPO	760	Other	0	12417	PCP	45176
KINGSTON ET LES ILES	19	86	No	LIB	7459	NPD	5106	PCP	4920	GPO	560	Other	0	18045	LIB	47947
KINGSTON ET LES ILES	23	86	No	LIB	8579	NPD	5862	PCP	5771	GPO	646	Other	0	20858	LIB	47947
LAMBTON KENT MIDDLESEX	19	77	No	PCP	8045	NPD	2723	LIB	1310	Other	1060	Other	0	13138	PCP	41372
LEEDS GRENVILLE THOUSAND ISLANDS ET RIDEAU LAKES	15	97	No	PCP	4539	LIB	1834	NPD	1393	GPO	577	Other	0	8343	PCP	41729

Constituency	Boxes Counted	Total Boxes	RDI Elected	First	First Count	Second	Second Count	Third	Third Count	Fourth	Fourth Count	Fifth	Fifth Count	Total Votes	End Winner	End Total Votes
LONDON CENTRE NORD	1	82	No	PCP	10	LIB	9	NPD	5	GPO	1	Other	0	25	NDP	42410
NEPEAN	3	51	No	PCP	67	LIB	43	NPD	25	Other	7	Other	0	142	PCP	43247
NEPEAN	19	51	No	PCP	3364	LIB	2797	NPD	1613	GPO	331	Other	0	8105	PCP	43247
NIPISSING	15	72	No	PCP	3832	NPD	2123	LIB	925	GPO	271	Other	0	7151	PCP	29848
ORLEANS	35	57	No	LIB	17575	PCP	12159	NPD	5412	GPO	1823	Other	0	36969	LIB	51213
OTTAWA CENTRE	1	120	No	NPD	237	LIB	195	PCP	125	GPO	50	Other	0	607	NDP	55196
OTTAWA OUEST NEPEAN	44	70	No	NPD	8563	PCP	8457	LIB	5317	GPO	972	Other	0	23309	NDP	41814
OTTAWA SUD	17	68	No	LIB	5758	NPD	3399	PCP	2872	GPO	637	Other	0	12666	LIB	39851
PARRY SOUND MUSKOKA	96	96	No	PCP	20216	GPO	18102	NPD	3391	Other	0	Other	0	41709	PCP	44277
PICKERING UXBRIDGE	17	55	No	PCP	6635	LIB	4448	NPD	2189	GPO	721	Other	0	13993	PCP	42543
RENFREW NIPISSING PEMBROKE	14	98	No	PCP	1998	NPD	781	LIB	371	Other	166	Other	0	3316	PCP	38701
SUDBURY	1	89	No	NPD	8	LIB	6	PCP	5	Other	1	Other	0	20	NDP	28463
VAUGHAN WOODBRIDGE	1	38	No	PCP	309	LIB	171	NPD	41	GPO	19	Other	0	540	PCP	35378
VAUGHAN WOODBRIDGE	15	38	No	PCP	7015	LIB	4422	NPD	725	Other	320	Other	0	12482	PCP	35378
WINDSOR TECUMSEH	37	69	No	PCP	13040	NPD	8855	LIB	4111	Other	875	Other	0	26881	PCP	37062
YORK SIMCOE	3	50	No	PCP	1975	LIB	602	GPO	269	NPD	246	Other	0	3092	PCP	35515
YORK SUD WESTON	56	73	No	PCP	10259	NPD	9516	LIB	6606	GPO	701	Other	0	27082	PCP	29972
ABITIBI-OUEST	40	139	Yes	CAQ	3876	PQ	1308	QS	849	PCQ	590	PLQ	404	7027	CAQ	22087
ACADIE	14	165	No	PLQ	828	CAQ	344	QS	274	PCQ	243	PQ	227	1916	PLQ	25415
ANJOU-LOUIS-RIEL	103	133	No	PLQ	5223	CAQ	4803	QS	2633	PQ	1656	PCQ	1323	15638	CAQ	26111
ANJOU-LOUIS-RIEL	115	133	No	PLQ	5844	CAQ	5430	QS	2838	PQ	1832	PCQ	1464	17408	CAQ	26111
ARGENTEUIL	31	177	Yes	CAQ	4120	PQ	1120	PLQ	952	PCQ	952	QS	575	7719	CAQ	31671
BEAUCE-NORD	1	151	No	CAQ	150	PCQ	112	PQ	18	PLQ	9	QS	4	293	CAQ	33445
BEAUCE-NORD	82	151	No	CAQ	8326	PCQ	7993	PQ	1081	QS	769	PLQ	498	18667	CAQ	33445
BEAUCE-NORD	149	151	No	CAQ	14365	PCQ	14148	PQ	1955	QS	1425	PLQ	912	32805	CAQ	33445
BEAUCE-SUD	90	180	No	CAQ	9148	PCQ	7916	PQ	809	QS	724	PLQ	598	19195	CAQ	36987
BEAUCE-SUD	171	180	No	CAQ	15819	PCQ	15373	QS	1427	PQ	1423	PLQ	995	35037	CAQ	36987
BERTRAND	6	181	No	CAQ	632	PQ	216	QS	149	PLQ	98	PCQ	78	1173	CAQ	34427
BONAVENTURE	1	134	No	CAQ	50	PQ	30	QS	8	PLQ	3	PCQ	3	94	CAQ	22174
BOURASSA-SAUVE	4	164	No	PLQ	214	CAQ	118	QS	77	PCQ	46	PQ	38	493	PLQ	23752
BROME-MISSISQUOI	4	233	No	CAQ	224	PCQ	69	QS	68	PQ	61	PLQ	45	467	CAQ	43292
CAMILLE-LAURIN	1	173	No	CAQ	128	PQ	91	PLQ	38	PCQ	18	Other	0	275	PQ	28358
CAMILLE-LAURIN	13	173	No	CAQ	1553	PQ	1262	PLQ	313	PCQ	187	Other	0	3315	PQ	28358
CAMILLE-LAURIN	40	173	No	PQ	3424	CAQ	3382	PLQ	1048	PCQ	495	Other	0	8349	PQ	28358
CAMILLE-LAURIN	55	173	No	PQ	4565	CAQ	4173	PLQ	1394	PCQ	676	Other	0	10808	PQ	28358
CAMILLE-LAURIN	67	173	No	PQ	5349	CAQ	4557	PLQ	1757	PCQ	798	Other	0	12461	PQ	28358
CAMILLE-LAURIN	83	173	No	PQ	6333	CAQ	5139	PLQ	2245	PCQ	976	Other	0	14693	PQ	28358
CAMILLE-LAURIN	96	173	No	PQ	7232	CAQ	5549	PLQ	2500	PCQ	1135	Other	0	16416	PQ	28358
CAMILLE-LAURIN	110	173	Yes	PQ	8067	CAQ	6098	PLQ	3003	PCQ	1260	Other	0	18428	PQ	28358
CHAPLEAU	19	189	Yes	CAQ	1869	PLQ	415	PCQ	281	QS	263	PQ	243	3071	CAQ	30945
CHARLEVOIX-COTE-DE-BEAUPRE	1	189	No	CAQ	358	QS	117	PQ	77	PCQ	51	PLQ	39	642	CAQ	37216
CHARLEVOIX-COTE-DE-BEAUPRE	21	189	Yes	CAQ	1468	QS	512	PQ	504	PCQ	324	PLQ	125	2933	CAQ	37216
CHAUVEAU	2	205	No	CAQ	450	PCQ	238	QS	50	PQ	46	PLQ	28	812	CAQ	42860
CHOMEDEY	1	205	No	CAQ	40	PLQ	19	PQ	7	PCQ	4	QS	3	73	PLQ	31971
CHOMEDEY	17	205	No	PLQ	1534	CAQ	1357	PCQ	711	PQ	339	QS	258	4199	PLQ	31971
CHOMEDEY	35	205	No	PLQ	2431	CAQ	1628	PCQ	1331	PQ	414	QS	356	6160	PLQ	31971
CHUTES-DE-LA-CHAUDIERE	8	203	No	CAQ	311	PCQ	131	PQ	52	QS	32	PLQ	17	543	CAQ	46467
CHUTES-DE-LA-CHAUDIERE	25	203	Yes	CAQ	1919	PCQ	1057	PQ	362	QS	281	PLQ	184	3803	CAQ	46467
CHUTES-DE-LA-CHAUDIERE	113	203	Yes	CAQ	10097	PCQ	5975	PQ	2447	QS	1930	PLQ	1132	21581	CAQ	46467
DEUX-MONTAGNES	6	165	No	CAQ	966	PQ	268	QS	189	PLQ	127	PCQ	122	1672	CAQ	33165
DRUMMOND-BOIS-FRANCS	24	177	Yes	CAQ	3329	PCQ	904	PQ	724	QS	397	PLQ	169	5523	CAQ	35844
DUBUC	1	146	No	CAQ	315	PQ	55	PCQ	53	QS	31	PLQ	9	463	CAQ	26581
DUBUC	32	146	Yes	CAQ	5453	PQ	1326	PCQ	815	QS	605	PLQ	244	8443	CAQ	26581
DUPLESSIS	4	158	No	QS	30	CAQ	29	PCQ	28	PLQ	20	PQ	10	117	CAQ	19273
DUPLESSIS	64	158	No	CAQ	2611	PQ	1690	PCQ	1250	QS	749	PLQ	328	6628	CAQ	19273
DUPLESSIS	99	158	Yes	CAQ	6174	PQ	3396	PCQ	2248	QS	1133	PLQ	602	13553	CAQ	19273
FABRE	10	177	No	CAQ	964	PLQ	553	PCQ	237	PQ	216	QS	170	2140	CAQ	33889
FABRE	173	177	No	CAQ	10693	PLQ	10395	PCQ	5107	QS	3556	PQ	3283	33034	CAQ	33889
GATINEAU	4	217	No	CAQ	133	PCQ	63	PLQ	62	QS	24	PQ	22	304	CAQ	36076
GOUIN	1	147	No	QS	263	CAQ	68	PQ	40	PLQ	32	PCQ	14	417	QS	28188
GOUIN	13	147	Yes	QS	1796	CAQ	494	PQ	455	PLQ	225	PCQ	93	3063	QS	28188
HOCHELAGA-MAISONNEUVE	30	137	Yes	QS	2073	CAQ	643	PQ	562	PLQ	339	PCQ	221	3838	QS	24645
HULL	1	193	No	CAQ	40	PLQ	26	PCQ	13	QS	8	Other	8	95	CAQ	31270
HULL	27	193	No	CAQ	895	PLQ	814	QS	664	PQ	295	PCQ	292	2960	CAQ	31270
HUNTINGDON	133	158	Yes	CAQ	9889	PLQ	3466	PCQ	3270	PQ	2749	QS	2579	21953	CAQ	28588
ILES-DE-LA-MADELEINE	2	53	No	PQ	125	CAQ	43	QS	11	PLQ	10	PCQ	1	190	PQ	8364
ILES-DE-LA-MADELEINE	14	53	No	CAQ	836	PQ	801	PLQ	145	QS	114	PCQ	12	1908	PQ	8364
ILES-DE-LA-MADELEINE	18	53	No	PQ	1209	CAQ	1013	PLQ	172	QS	145	PCQ	21	2560	PQ	8364
ILES-DE-LA-MADELEINE	32	53	No	PQ	2320	CAQ	1943	PLQ	420	QS	241	PCQ	53	4977	PQ	8364
ILES-DE-LA-MADELEINE	46	53	Yes	PQ	3515	CAQ	3054	PLQ	560	QS	362	PCQ	84	7575	PQ	8364
JACQUES-CARTIER	14	163	Yes	PLQ	1777	CAQ	363	PCQ	283	PQ	116	QS	110	2649	PLQ	27071
JEAN-LESAGE	8	161	No	QS	87	CAQ	35	PQ	19	PCQ	12	PLQ	5	158	QS	29737
JEAN-LESAGE	81	161	Yes	QS	3930	CAQ	2643	PCQ	1506	PQ	1140	PLQ	406	9625	QS	29737
JEANNE-MANCE-VIGER	19	164	Yes	PLQ	1790	CAQ	749	PCQ	411	QS	317	PQ	193	3460	PLQ	26019
JOLIETTE	24	221	No	CAQ	2153	PQ	1451	QS	439	PCQ	342	PLQ	142	4527	CAQ	39330
JOLIETTE	78	221	No	CAQ	5305	PQ	4054	QS	1381	PCQ	1139	PLQ	354	12233	CAQ	39330
JONQUIERE	6	160	No	CAQ	609	PQ	186	PCQ	66	QS	61	PLQ	17	939	CAQ	30460
JONQUIERE	15	160	Yes	CAQ	1502	PQ	440	PCQ	160	QS	127	PLQ	91	2320	CAQ	30460
JONQUIERE	18	160	Yes	CAQ	2298	PQ	657	PCQ	264	QS	190	PLQ	115	3524	CAQ	30460
JONQUIERE	151	160	Yes	CAQ	17308	PQ	5602	PCQ	2771	QS	2461	PLQ	615	28757	CAQ	30460
L'ASSOMPTION	8	156	Yes	CAQ	1715	PQ	309	QS	199	PCQ	111	PLQ	94	2428	CAQ	31790
LA PRAIRIE	2	161	No	CAQ	66	PLQ	22	QS	20	PQ	20	PCQ	10	138	CAQ	34252
LAPORTE	7	187	No	CAQ	850	PLQ	505	QS	233	PQ	207	PCQ	108	1903	CAQ	32632
LAPORTE	122	187	No	PLQ	6297	CAQ	6125	QS	3532	PQ	2381	PCQ	1517	19852	CAQ	32632
LAPORTE	174	187	No	CAQ	9758	PLQ	9175	QS	5352	PQ	3809	PCQ	2286	30380	CAQ	32632
LAURIER-DORION	15	150	No	QS	756	PLQ	603	CAQ	241	PCQ	209	PQ	173	1982	QS	26182
LAURIER-DORION	21	150	No	QS	1125	PLQ	833	CAQ	368	PQ	283	PCQ	259	2868	QS	26182
LAVAL-DES-RAPIDES	8	184	No	CAQ	846	PLQ	443	PQ	315	QS	284	PCQ	121	2009	CAQ	32832
LAVAL-DES-RAPIDES	144	184	Yes	CAQ	8014	PLQ	7524	QS	4201	PQ	3387	PCQ	2292	25418	CAQ	32832
LEVIS	17	185	No	CAQ	1374	PCQ	234	PLQ	222	PQ	189	QS	136	2155	CAQ	36646
LEVIS	19	185	Yes	CAQ	1643	PCQ	366	PQ	273	PLQ	244	QS	186	2712	CAQ	36646
LOTBINIERE-FRONTENAC	3	209	No	PCQ	292	CAQ	252	PLQ	50	QS	40	PQ	36	670	CAQ	41929
LOTBINIERE-FRONTENAC	13	209	No	CAQ	1340	PCQ	554	PLQ	192	QS	179	PQ	153	2418	CAQ	41929
LOUIS-HEBERT	4	164	No	CAQ	229	PCQ	103	PQ	29	QS	22	PLQ	18	401	CAQ	37360
MARGUERITE-BOURGEOYS	40	174	No	PLQ	3883	CAQ	3285	PQ	817	QS	805	PCQ	784	9574	PLQ	27135
MARIE-VICTORIN	6	151	No	CAQ	587	PQ	321	QS	152	PLQ	92	PCQ	49	1201	CAQ	27177
MARIE-VICTORIN	57	151	No	CAQ	4176	PQ	2827	QS	2155	PLQ	1071	PCQ	703	10932	CAQ	27177
MARQUETTE	1	157	No	CAQ	85	PLQ	80	QS	28	PQ	27	PCQ	22	242	PLQ	25442
MARQUETTE	2	157	No	CAQ	85	PLQ	80	QS	28	PQ	27	PCQ	22	242	PLQ	25442
MARQUETTE	41	157	No	PLQ	2510	CAQ	995	PCQ	583	QS	473	PQ	323	4884	PLQ	25442
MARQUETTE	43	157	No	PLQ	2693	CAQ	1011	PCQ	611	QS	491	PQ	334	5140	PLQ	25442
MASSON	151	159	Yes	CAQ	17512	PQ	6156	QS	4309	PCQ	2850	PLQ	2620	33447	CAQ	34932
MATANE-MATAPEDIA	9	179	Yes	PQ	1104	CAQ	346	PCQ	79	QS	68	PLQ	37	1634	PQ	29623
MATANE-MATAPEDIA	81	179	Yes	PQ	9252	CAQ	2328	PCQ	991	QS	548	PLQ	254	13373	PQ	29623
MAURICE-RICHARD	5	165	No	QS	330	CAQ	290	PQ	168	PLQ	141	PCQ	33	962	QS	30793
MAURICE-RICHARD	33	165	No	QS	2398	CAQ	2363	PQ	1196	PLQ	949	PCQ	251	7157	QS	30793
MAURICE-RICHARD	34	165	No	QS	2449	CAQ	2394	PQ	1208	PLQ	996	PCQ	259	7306	QS	30793
MEGANTIC	3	149	No	CAQ	442	PCQ	144	PQ	94	QS	91	PLQ	30	801	CAQ	28009
MEGANTIC	136	149	Yes	CAQ	11958	PCQ	5945	PQ	3366	QS	3183	PLQ	1509	25961	CAQ	28009

Constituency	Boxes Counted	Total Boxes	RDI Elected	First	First Count	Second	Second Count	Third	Third Count	Fourth	Fourth Count	Fifth	Fifth Count	Total Votes	End Winner	End Total Votes
MERCIER	37	154	Yes	QS	2299	PLQ	774	PQ	646	CAQ	557	PCQ	185	4461	QS	26443
MILLE-ILES	10	149	No	CAQ	1495	PLQ	967	PQ	544	PCQ	347	QS	334	3687	PLQ	29064
MILLE-ILES	144	149	No	PLQ	9140	CAQ	8535	QS	3496	PQ	3357	PCQ	2996	27524	PLQ	29064
MONT-ROYAL-OUTREMONT	16	208	No	PLQ	74	QS	15	PCQ	10	CAQ	5	PQ	2	106	PLQ	28250
MONT-ROYAL-OUTREMONT	21	208	No	PLQ	74	QS	15	PCQ	10	CAQ	5	PQ	2	106	PLQ	28250
MONT-ROYAL-OUTREMONT	30	208	No	PLQ	462	QS	208	CAQ	145	PQ	136	PCQ	61	1012	PLQ	28250
MONT-ROYAL-OUTREMONT	42	208	Yes	PLQ	1111	QS	407	CAQ	385	PQ	269	PCQ	202	2374	PLQ	28250
NELLIGAN	15	182	Yes	PLQ	2057	CAQ	937	PCQ	540	PQ	233	QS	211	3978	PLQ	31264
NOTRE-DAME-DE-GRACE	16	159	Yes	PLQ	1989	QS	508	CAQ	355	PCQ	256	PQ	239	3347	PLQ	22550
PONTIAC	2	187	No	PLQ	80	PCQ	27	CAQ	12	Other	11	Other	7	137	PLQ	27473
PONTIAC	10	187	No	PLQ	660	PCQ	134	CAQ	83	Other	58	Other	20	955	PLQ	27473
PONTIAC	20	187	Yes	PLQ	1192	CAQ	353	PCQ	262	QS	92	Other	72	1971	PLQ	27473
PREVOST	26	165	No	CAQ	1459	PQ	687	QS	597	PCQ	390	PLQ	246	3379	CAQ	33927
RENE-LEVESQUE	27	121	No	CAQ	2016	PQ	830	PCQ	378	QS	308	PLQ	59	3591	CAQ	19185
RENE-LEVESQUE	48	121	Yes	CAQ	4183	PQ	1534	PCQ	737	QS	550	PLQ	119	7123	CAQ	19185
RIMOUSKI	135	167	No	CAQ	8996	PQ	6695	QS	4767	PCQ	1065	PLQ	624	22147	CAQ	32801
ROBERT-BALDWIN	21	174	Yes	PLQ	3415	CAQ	882	PCQ	777	QS	280	PQ	227	5581	PLQ	27645
ROSEMONT	1	186	No	CAQ	200	QS	161	PQ	135	PLQ	48	Other	21	565	QS	34770
ROSEMONT	24	186	No	QS	2060	CAQ	1718	PQ	1360	PLQ	547	PCQ	206	5891	QS	34770
ROSEMONT	35	186	No	QS	3032	CAQ	2157	PQ	1824	PLQ	725	PCQ	300	8038	QS	34770
ROSEMONT	61	186	No	QS	4880	CAQ	3360	PQ	3025	PLQ	1352	PCQ	534	13151	QS	34770
ROSEMONT	67	186	Yes	QS	5329	CAQ	3497	PQ	3223	PLQ	1473	PCQ	576	14098	QS	34770
ROUSSEAU	9	157	Yes	CAQ	1012	PQ	330	PCQ	180	QS	132	PLQ	46	1700	CAQ	27912
ROUYN-NORANDA-TEMISCAMINGUE	38	166	No	CAQ	2497	QS	1565	PQ	563	PCQ	506	PLQ	385	5516	CAQ	28554
ROUYN-NORANDA-TEMISCAMINGUE	83	166	No	CAQ	5521	QS	3872	PQ	1403	PCQ	1124	PLQ	666	12586	CAQ	28554
ROUYN-NORANDA-TEMISCAMINGUE	86	166	Yes	CAQ	5687	QS	3990	PQ	1449	PCQ	1159	PLQ	678	12963	CAQ	28554
ROUYN-NORANDA-TEMISCAMINGUE	132	166	Yes	CAQ	10187	QS	6822	PQ	2551	PCQ	1849	PLQ	1005	22414	CAQ	28554
SAINT-FRANCOIS	1	205	No	CAQ	67	PCQ	28	QS	23	PQ	15	PLQ	6	139	CAQ	40186
SAINT-FRANCOIS	6	205	No	CAQ	335	QS	220	PLQ	194	PCQ	98	PQ	66	913	CAQ	40186
SAINT-FRANCOIS	94	205	No	CAQ	7519	QS	4851	PCQ	1832	PQ	1549	PLQ	1514	17265	CAQ	40186
SAINT-HENRI-SAINTE-ANNE	1	197	No	PLQ	49	QS	29	Other	4	CAQ	3	PQ	3	88	PLQ	31217
SAINT-HENRI-SAINTE-ANNE	123	197	Yes	PLQ	7554	QS	5976	CAQ	3864	PQ	1792	PCQ	1257	20443	PLQ	31217
SAINT-HENRI-SAINTE-ANNE	171	197	Yes	PLQ	10352	QS	7906	CAQ	5080	PQ	2384	PCQ	1830	27552	PLQ	31217
SAINT-JEAN	197	215	Yes	CAQ	18739	PQ	7239	QS	5495	PCQ	3168	PLQ	2235	36876	CAQ	42484
SAINT-LAURENT	5	192	No	PLQ	339	PCQ	88	CAQ	72	QS	48	PQ	21	568	PLQ	26904
SAINT-LAURENT	16	192	Yes	PLQ	963	PCQ	281	CAQ	220	QS	190	PQ	96	1750	PLQ	26904
SAINTE-MARIE-SAINT-JACQUES	1	158	No	QS	152	PQ	125	CAQ	86	PLQ	52	PCQ	18	433	QS	22281
SAINTE-MARIE-SAINT-JACQUES	17	158	Yes	QS	878	PQ	363	CAQ	307	PLQ	292	PCQ	100	1940	QS	22281
SAINTE-ROSE	28	182	Yes	CAQ	3730	PLQ	1432	PQ	868	QS	718	PCQ	513	7261	CAQ	36077
SAINTE-ROSE	166	182	Yes	CAQ	13267	PLQ	8018	QS	4606	PQ	4210	PCQ	3162	33263	CAQ	36077
SHERBROOKE	75	186	No	QS	4834	CAQ	3219	PQ	988	PCQ	835	PLQ	570	10446	QS	36664
SHERBROOKE	121	186	No	QS	8763	CAQ	7692	PQ	2001	PCQ	1579	PLQ	1229	21264	QS	36664
SOULANGES	183	199	Yes	CAQ	14989	PLQ	8187	PCQ	4633	QS	3858	PQ	3665	35332	CAQ	39358
TASCHEREAU	42	178	Yes	QS	2534	PQ	1329	CAQ	1298	PCQ	560	PLQ	346	6067	QS	33919
TROIS-RIVIERES	20	191	Yes	CAQ	1096	QS	188	PQ	180	PCQ	156	PLQ	84	1704	CAQ	36859
TROIS-RIVIERES	62	191	Yes	CAQ	4812	QS	1212	PQ	1116	PCQ	985	PLQ	529	8654	CAQ	36859
UNGAVA	2	111	No	CAQ	30	PLQ	26	PCQ	5	PQ	4	QS	2	67	CAQ	8635
UNGAVA	10	111	No	CAQ	136	PQ	48	PLQ	33	PCQ	29	QS	26	272	CAQ	8635
UNGAVA	86	111	No	CAQ	2477	QS	1450	PQ	837	PLQ	812	PCQ	625	6201	CAQ	8635
VANIER-LES RIVIERES	199	203	Yes	CAQ	20142	PCQ	8291	PQ	5550	QS	4990	PLQ	2651	41624	CAQ	43222
VERDUN	8	162	No	PLQ	264	QS	217	CAQ	199	PQ	72	PCQ	36	788	QS	30068
VERDUN	9	162	No	PLQ	304	QS	265	CAQ	218	PQ	81	PCQ	40	908	QS	30068
VERDUN	40	162	No	PLQ	1620	QS	1539	CAQ	1123	PQ	403	PCQ	349	5034	QS	30068
VERDUN	121	162	No	QS	6378	PLQ	5319	CAQ	3749	PQ	1500	PCQ	1140	18086	QS	30068
VERDUN	135	162	No	QS	6672	PLQ	6508	CAQ	4625	PQ	1726	PCQ	1282	20813	QS	30068
VERDUN	136	162	No	QS	6905	PLQ	6596	CAQ	4718	PQ	1752	PCQ	1295	21266	QS	30068
VERDUN	142	162	No	PLQ	7303	QS	7082	CAQ	5323	PQ	1981	PCQ	1386	23075	QS	30068
VERDUN	152	162	No	PLQ	8267	QS	8168	CAQ	6363	PQ	2334	PCQ	1522	26654	QS	30068
VIAU	16	132	No	PLQ	1440	QS	1074	CAQ	814	PQ	358	PCQ	212	3898	PLQ	20560
VIMONT	18	153	No	PLQ	1122	CAQ	808	PCQ	511	QS	346	PQ	279	3066	CAQ	31664
VIMONT	64	153	No	CAQ	4170	PLQ	4160	PCQ	1754	QS	1458	PQ	1342	12884	CAQ	31664
VIMONT	147	153	Yes	CAQ	10660	PLQ	9294	PCQ	4034	QS	3462	PQ	3263	30713	CAQ	31664
WESTMOUNT-SAINT-LOUIS	2	178	No	PLQ	20	PCQ	11	QS	6	CAQ	3	Other	2	42	PLQ	18572
ABITIBI BAIE JAMES NUNAVIK EEYOU	10	197	False	BQ	239	LPC	223	CPC	141	NDP	107	Other	0	710	BQ	31656
ABITIBI BAIE JAMES NUNAVIK EEYOU	110	197	False	BQ	6529	LPC	4608	CPC	3043	NDP	1814	Other	0	15994	BQ	31656
ABITIBI TEMISCAMINGUE	1	270	False	BQ	38	CPC	19	LPC	16	GPC	13	Other	0	86	BQ	50155
ABITIBI TEMISCAMINGUE	15	270	False	BQ	702	LPC	457	CPC	303	NDP	196	Other	0	1658	BQ	50155
ABITIBI TEMISCAMINGUE	75	270	False	BQ	4673	LPC	2695	CPC	1792	NDP	1326	Other	0	10486	BQ	50155
AHUNTSIC CARTIERVILLE	1	231	False	LPC	22	BQ	2	CPC	1	GPC	1	Other	0	26	LPC	55111
AVALON	25	213	False	LPC	1316	CPC	889	NDP	258	GPC	130	Other	0	2593	LPC	41334
BEAUCE	7	242	False	CPC	762	PPC	521	BQ	354	LPC	243	Other	0	1880	CPC	59429
BEAUCE	65	242	False	CPC	7919	PPC	5789	BQ	2836	LPC	2440	Other	0	18984	CPC	59429
BEAUCE	205	242	False	CPC	19871	PPC	14576	BQ	7079	LPC	5813	Other	0	47339	CPC	59429
BEAUPORT COTE DE BEAUPRE ILE D'ORLEANS CHARLEVOIX	1	246	False	BQ	184	LPC	70	CPC	62	NDP	12	Other	0	328	BQ	50635
BEAUPORT LIMOILOU	130	200	False	BQ	7556	LPC	6478	CPC	6340	NDP	2963	Other	0	23337	BQ	50191
BEAUSEJOUR	1	221	False	LPC	474	GPC	168	CPC	136	NDP	39	Other	0	817	LPC	53685
BEAUSEJOUR	5	221	False	LPC	661	GPC	319	CPC	229	NDP	86	Other	0	1295	LPC	53685
BEAUSEJOUR	30	221	False	LPC	2086	GPC	1472	CPC	778	NDP	282	Other	0	4618	LPC	53685
BECANCOUR NICOLET SAUREL	1	237	False	BQ	36	LPC	27	CPC	4	NDP	0	Other	0	67	BQ	52337
BELOEIL CHAMBLY	1	270	False	BQ	239	LPC	88	NDP	77	CPC	27	Other	0	431	BQ	69490
BELOEIL CHAMBLY	12	270	False	BQ	1527	LPC	821	NDP	409	CPC	269	Other	0	3026	BQ	69490
BELOEIL CHAMBLY	27	270	False	BQ	3359	LPC	1646	NDP	974	CPC	481	Other	0	6460	BQ	69490
BERTHIER MASKINONGE	1	273	False	LPC	10	BQ	8	CPC	2	NDP	0	Other	0	20	BQ	56354
BERTHIER MASKINONGE	3	273	False	NDP	124	BQ	76	LPC	38	CPC	19	Other	0	257	BQ	56354
BERTHIER MASKINONGE	215	273	False	BQ	13673	NDP	12734	LPC	5060	CPC	3581	Other	0	35048	BQ	56354
BERTHIER MASKINONGE	221	273	False	BQ	14315	NDP	13946	LPC	5440	CPC	3972	Other	0	37673	BQ	56354
BERTHIER MASKINONGE	248	273	False	BQ	17864	NDP	17069	LPC	6642	CPC	4896	Other	0	46471	BQ	56354
BERTHIER MASKINONGE	253	273	False	BQ	18413	NDP	17424	LPC	6836	CPC	5028	Other	0	47701	BQ	56354
BONAVISTA BURIN TRINITY	90	260	False	LPC	3790	CPC	3058	NDP	842	GPC	258	Other	0	7948	LPC	32179
BROME MISSISQUOI	1	266	False	BQ	98	LPC	78	CPC	53	GPC	20	Other	0	249	LPC	61441
BROME MISSISQUOI	18	266	False	BQ	1034	LPC	948	CPC	458	NDP	225	Other	0	2665	LPC	61441
BROME MISSISQUOI	125	266	False	LPC	7640	BQ	7271	CPC	2788	NDP	1842	Other	0	19541	LPC	61441
BROME MISSISQUOI	202	266	False	LPC	15444	BQ	13813	CPC	4944	NDP	3270	Other	0	37471	LPC	61441
BURNABY SUD	73	192	False	NDP	4536	CPC	3826	LPC	2993	GPC	714	Other	0	12069	NDP	45006
BURNABY SUD	75	192	False	NDP	4627	CPC	3900	LPC	3047	GPC	730	Other	0	12304	NDP	45006
CAPE BRETON CANSO	2	216	False	CPC	120	LPC	117	NDP	67	GPC	21	Other	0	325	LPC	42940
CAPE BRETON CANSO	90	216	False	LPC	5961	CPC	5522	NDP	2307	GPC	1278	Other	0	15068	LPC	42940
CARDIGAN	6	90	False	LPC	1307	CPC	796	GPC	359	NDP	139	Other	0	2601	LPC	22167
CARDIGAN	12	90	False	LPC	1687	CPC	1021	GPC	453	NDP	185	Other	0	3346	LPC	22167
CHARLESBOURG HAUTE SAINT CHARLES	20	229	False	CPC	1053	BQ	735	LPC	557	NDP	252	Other	0	2597	CPC	59096

Constituency	Boxes Counted	Total Boxes	RDI Elected	First	First Count	Second	Second Count	Third	Third Count	Fourth	Fourth Count	Fifth	Fifth Count	Total Votes	End Winner	End Total Votes
CHARLESBOURG HAUTE SAINT CHARLES	40	229	False	CPC	2324	BQ	1541	LPC	1287	NDP	542	Other	0	5694	CPC	59096
CHARLOTTETOWN	1	77	False	LPC	38	CPC	31	GPC	11	NDP	3	Other	0	83	LPC	19910
CHATEAUGUAY LACOLLE	12	220	False	LPC	663	BQ	467	CPC	184	NDP	54	Other	0	1368	LPC	52402
CHATEAUGUAY LACOLLE	201	220	False	LPC	17860	BQ	16900	CPC	5217	NDP	3473	Other	0	43450	LPC	52402
CHATEAUGUAY LACOLLE	210	220	False	LPC	19262	BQ	18643	CPC	5638	NDP	3764	Other	0	47307	LPC	52402
COAST OF BAYS CENTRAL NOTRE DAME	40	231	False	LPC	1903	CPC	1222	NDP	307	GPC	114	Other	0	3546	LPC	34182
COMPTON STANSTEAD	170	269	False	LPC	11404	BQ	9539	CPC	4449	NDP	3035	Other	0	28427	LPC	58237
COMPTON STANSTEAD	215	269	False	LPC	15510	BQ	13331	CPC	6169	NDP	4016	Other	0	39026	LPC	58237
CUMBERLAND COLCHESTER	1	221	False	CPC	43	LPC	27	NDP	13	GPC	0	Other	0	83	LPC	45450
CUMBERLAND COLCHESTER	102	220	False	LPC	5728	CPC	5547	GPC	2041	NDP	1879	Other	0	15195	LPC	45450
DARTMOUTH COLE HARBOUR	1	198	False	NDP	71	LPC	69	CPC	28	GPC	23	Other	0	191	LPC	53499
DRUMMOND	2	241	False	BQ	185	CPC	70	LPC	64	NDP	54	Other	0	373	BQ	54824
DRUMMOND	115	241	False	BQ	10074	LPC	3970	CPC	3563	NDP	3496	Other	0	21103	BQ	54824
EGMONT	1	90	False	CPC	41	LPC	30	GPC	18	NDP	6	Other	0	95	LPC	20178
FREDERICTON	10	158	False	CPC	523	GPC	511	LPC	451	NDP	73	Other	0	1558	GPC	49409
FREDERICTON	15	158	False	GPC	806	CPC	719	LPC	677	NDP	120	Other	0	2322	GPC	49409
FREDERICTON	52	158	False	GPC	3870	CPC	3290	LPC	2961	NDP	714	Other	0	10835	GPC	49409
FREDERICTON	133	158	False	GPC	11665	CPC	10265	LPC	9340	NDP	2087	Other	0	33357	GPC	49409
FUNDY ROYAL	2	198	False	CPC	66	LPC	40	GPC	20	Other	3	Other	0	129	CPC	48646
FUNDY ROYAL	25	198	False	CPC	1723	LPC	1015	GPC	591	NDP	374	Other	0	3703	CPC	48646
GASPESIE LES ILES DE LA MADELEINE	2	214	False	BQ	122	LPC	108	CPC	23	NDP	10	Other	0	263	LPC	38380
GASPESIE LES ILES DE LA MADELEINE	10	214	False	BQ	871	LPC	869	CPC	218	NDP	59	Other	0	2017	LPC	38380
GASPESIE LES ILES DE LA MADELEINE	25	214	False	BQ	1899	LPC	1636	CPC	383	NDP	123	Other	0	4041	LPC	38380
GASPESIE LES ILES DE LA MADELEINE	140	214	False	BQ	9173	LPC	9134	CPC	1753	NDP	890	Other	0	20950	LPC	38380
GASPESIE LES ILES DE LA MADELEINE	189	214	False	LPC	13719	BQ	13371	CPC	2643	NDP	1398	Other	0	31131	LPC	38380
GASPESIE LES ILES DE LA MADELEINE	207	214	False	LPC	14595	BQ	14503	CPC	2780	NDP	1504	Other	0	33382	LPC	38380
GASPESIE LES ILES DE LA MADELEINE	212	214	False	LPC	16093	BQ	15464	CPC	2993	NDP	1640	Other	0	36190	LPC	38380
HALIFAX OUEST	30	225	False	LPC	2190	NDP	897	CPC	851	GPC	567	Other	0	4505	LPC	54357
HOCHELAGA	35	219	False	LPC	2235	BQ	1865	NDP	1137	CPC	318	Other	0	5555	LPC	53037
HOCHELAGA	70	219	False	LPC	5003	BQ	4224	NDP	2932	CPC	660	Other	0	12819	LPC	53037
HOCHELAGA	140	219	False	LPC	9850	BQ	8717	NDP	5933	CPC	1305	Other	0	25805	LPC	53037
HONORE MERCIER	1	209	False	LPC	56	BQ	26	CPC	14	NDP	6	Other	0	102	LPC	50363
HONORE MERCIER	25	209	False	LPC	3136	BQ	1335	CPC	481	NDP	408	Other	0	5360	LPC	50363
JOLIETTE	1	271	False	BQ	264	LPC	72	CPC	38	NDP	24	Other	0	398	BQ	57699
JONQUIERE	1	210	False	BQ	108	CPC	94	NDP	54	LPC	47	Other	0	303	BQ	49367
JONQUIERE	2	210	False	BQ	216	CPC	177	NDP	105	LPC	94	Other	0	592	BQ	49367
JONQUIERE	15	210	False	BQ	1077	NDP	620	CPC	614	LPC	568	Other	0	2879	BQ	49367
JONQUIERE	55	210	False	BQ	4693	NDP	3150	CPC	2613	LPC	2239	Other	0	12695	BQ	49367
LA POINTE DE L'ILE	10	243	False	BQ	1025	LPC	596	NDP	210	CPC	147	Other	0	1978	BQ	55534
LA PRAIRIE	119	204	False	BQ	15166	LPC	12731	CPC	3010	NDP	2872	Other	0	33779	BQ	61553
LABRADOR	25	90	False	LPC	896	CPC	474	NDP	330	GPC	30	Other	0	1730	LPC	11419
LAC SAINT JEAN	1	267	False	BQ	72	CPC	20	LPC	17	NDP	4	Other	0	113	BQ	54227
LAC SAINT JEAN	60	267	False	BQ	4543	LPC	2355	CPC	2325	NDP	546	Other	0	9769	BQ	54227
LAC SAINT JEAN	80	267	False	BQ	6212	CPC	3234	LPC	3117	NDP	717	Other	0	13280	BQ	54227
LASALLE EMARD VERDUN	95	203	False	LPC	10547	BQ	5805	NDP	3521	CPC	1941	Other	0	21814	LPC	52391
LAURENTIDES LABELLE	5	284	False	BQ	208	LPC	198	CPC	49	NDP	22	Other	0	477	BQ	65406
LAURIER SAINTE MARIE	2	174	False	BQ	108	LPC	95	CPC	13	NDP	0	Other	0	216	LPC	53409
LAURIER SAINTE MARIE	9	174	False	LPC	641	BQ	550	NDP	178	CPC	51	Other	0	1420	LPC	53409
LAURIER SAINTE MARIE	19	174	False	LPC	1687	BQ	979	NDP	727	GPC	156	Other	0	3549	LPC	53409
LAURIER SAINTE MARIE	30	174	False	LPC	2829	BQ	1599	NDP	1549	GPC	335	Other	0	6312	LPC	53409
LONG RANGE MOUNTAINS	35	250	False	LPC	1543	CPC	1025	NDP	494	GPC	115	Other	0	3177	LPC	38426
LONGUEUIL CHARLES LEMOYNE	20	230	False	BQ	1193	LPC	1142	NDP	291	CPC	208	Other	0	2834	LPC	51544
LONGUEUIL CHARLES LEMOYNE	196	230	False	LPC	15988	BQ	15053	NDP	4333	CPC	2986	Other	0	38360	LPC	51544
LONGUEUIL SAINT HUBERT	1	226	False	LPC	18	BQ	12	GPC	3	NDP	1	Other	0	34	BQ	59844
LOUIS HEBERT	1	225	False	LPC	42	CPC	15	BQ	6	GPC	2	Other	0	65	LPC	62060
LOUIS HEBERT	15	225	False	LPC	851	BQ	422	CPC	276	NDP	115	Other	0	1664	LPC	62060
LOUIS SAINT LAURENT	5	255	False	CPC	224	BQ	140	LPC	125	NDP	19	Other	0	508	CPC	65561
LOUIS SAINT LAURENT	24	255	False	CPC	1557	BQ	871	LPC	811	NDP	288	Other	0	3527	CPC	65561
LOUIS SAINT LAURENT	40	255	False	CPC	2895	BQ	1582	LPC	1561	NDP	530	Other	0	6568	CPC	65561
MARKHAM STOUFFVILLE	20	238	False	LPC	1441	CPC	1326	Other	906	NDP	222	Other	0	3895	LPC	64388
MARKHAM STOUFFVILLE	40	238	False	LPC	3388	CPC	2952	Other	2164	NDP	516	Other	0	9020	LPC	64388
MARKHAM STOUFFVILLE	150	238	False	LPC	15374	CPC	12358	Other	9079	NDP	2468	Other	0	39279	LPC	64388
MIRAMICHI GRAND LAKE	1	163	False	CPC	22	LPC	19	NDP	7	GPC	4	Other	0	52	LPC	34598
MIRAMICHI GRAND LAKE	16	163	False	CPC	1021	LPC	711	GPC	233	NDP	189	Other	0	2154	LPC	34598
MIRAMICHI GRAND LAKE	65	163	False	CPC	3677	LPC	3641	GPC	1123	NDP	754	Other	0	9195	LPC	34598
MISSION MATSQUI FRASER CANYON	1	179	False	CPC	51	NDP	28	GPC	27	LPC	25	Other	0	131	CPC	46066
MONCTON RIVERVIEW DIEPPE	5	191	False	LPC	630	GPC	326	CPC	292	NDP	152	Other	0	1400	LPC	51828
MONCTON RIVERVIEW DIEPPE	25	191	False	LPC	1972	CPC	948	GPC	838	NDP	517	Other	0	4275	LPC	51828
MONCTON RIVERVIEW DIEPPE	50	191	False	LPC	3736	CPC	2032	GPC	1607	NDP	1128	Other	0	8503	LPC	51828
MONTARVILLE	10	211	False	BQ	620	LPC	525	NDP	114	CPC	105	Other	0	1364	BQ	59228
MONTARVILLE	25	211	False	BQ	1805	LPC	1498	NDP	341	CPC	316	Other	0	3960	BQ	59228
MONTARVILLE	105	211	False	BQ	8643	LPC	7534	NDP	1911	CPC	1408	Other	0	19496	BQ	59228
NANAIMO LADYSMITH	6	256	False	GPC	1004	CPC	783	NDP	683	LPC	319	Other	0	2789	GPC	71864
NANAIMO LADYSMITH	27	256	False	GPC	2178	CPC	1877	NDP	1402	LPC	872	Other	0	6329	GPC	71864
NOTRE DAME DE GRACE WESTMOUNT	70	206	False	LPC	6466	NDP	1817	CPC	1497	GPC	1089	Other	0	10869	LPC	50321
NOUVEAU BRUNSWICK SUD OUEST	35	180	False	CPC	2981	LPC	1756	GPC	731	NDP	368	Other	0	5836	CPC	39578
NOVA CENTRE	5	230	False	LPC	107	CPC	46	GPC	32	NDP	24	Other	0	209	LPC	44470
NOVA CENTRE	145	230	False	LPC	9866	CPC	6360	NDP	2894	GPC	1495	Other	0	20615	LPC	44470
NOVA OUEST	50	229	False	CPC	3383	LPC	2668	GPC	840	NDP	763	Other	0	7654	CPC	46798
NOVA OUEST	155	229	False	CPC	11774	LPC	10457	GPC	3507	NDP	2989	Other	0	28727	CPC	46798
OTTAWA CENTRE	70	250	False	LPC	7127	NDP	4604	CPC	1991	GPC	1112	Other	0	14834	LPC	78902
PAPINEAU	1	197	False	LPC	132	NDP	20	BQ	14	CPC	12	Other	0	178	LPC	50781
PAPINEAU	22	197	False	LPC	2017	NDP	775	BQ	544	GPC	355	Other	0	3691	LPC	50781
PIERRE BOUCHER LES PATRIOTES VERCHERES	1	227	False	LPC	21	BQ	16	GPC	2	PPC	2	Other	0	41	BQ	60783
QUEBEC	10	227	False	LPC	394	BQ	186	CPC	86	NDP	13	Other	0	679	LPC	54198
QUEBEC	160	227	False	LPC	9492	BQ	8723	CPC	4080	NDP	3350	Other	0	25645	LPC	54198
QUEBEC	216	227	False	LPC	14842	BQ	14394	CPC	6867	NDP	5380	Other	0	41483	LPC	54198
QUEBEC	224	227	False	LPC	17014	BQ	16867	CPC	7869	NDP	5897	Other	0	47647	LPC	54198
REGINA QU'APPELLE	1	167	False	CPC	91	LPC	11	NDP	10	GPC	1	Other	0	113	CPC	38755
REGINA QU'APPELLE	19	167	False	CPC	1364	NDP	496	LPC	408	GPC	84	Other	0	2352	CPC	38755
REGINA WASCANA	11	141	False	CPC	829	LPC	638	NDP	235	GPC	56	Other	0	1758	CPC	45355
REGINA WASCANA	98	141	False	CPC	10928	LPC	7332	NDP	3016	GPC	664	Other	0	21940	CPC	45355
RICHMOND ARTHABASKA	1	270	False	LPC	74	CPC	42	BQ	31	PPC	5	Other	0	152	CPC	58638

Constituency	Boxes Counted	Total Boxes	RDI Elected	First	First Count	Second	Second Count	Third	Third Count	Fourth	Fourth Count	Fifth	Fifth Count	Total Votes	End Winner	End Total Votes
RICHMOND ARTHABASKA	5	270	False	CPC	266	BQ	194	LPC	181	GPC	48	Other	0	689	CPC	58638
RICHMOND ARTHABASKA	25	270	False	CPC	1433	BQ	913	LPC	727	GPC	192	Other	0	3265	CPC	58638
RICHMOND ARTHABASKA	45	270	False	CPC	2979	BQ	1850	LPC	1152	GPC	369	Other	0	6350	CPC	58638
RIMOUSKI NEIGETTE TEMISCOUATA LES BASQUES	1	220	False	LPC	33	BQ	13	CPC	9	NDP	4	Other	0	59	BQ	45767
RIMOUSKI NEIGETTE TEMISCOUATA LES BASQUES	145	220	False	BQ	10266	NDP	7719	LPC	5853	CPC	2123	Other	0	25961	BQ	45767
RIVIERE DES MILLE ILES	150	227	False	BQ	11570	LPC	10360	NDP	2558	CPC	2278	Other	0	26766	BQ	58184
RIVIERE DU NORD	30	272	False	BQ	2021	LPC	1003	CPC	453	NDP	332	Other	0	3809	BQ	60101
RIVIERE DU NORD	90	272	False	BQ	7177	LPC	3087	CPC	1634	NDP	1109	Other	0	13007	BQ	60101
ROSEMONT LA PETITE PATRIE	1	223	False	LPC	30	BQ	5	NDP	4	Other	2	Other	0	41	NDP	60206
ROSEMONT LA PETITE PATRIE	11	223	False	NDP	1192	LPC	613	BQ	589	GPC	168	Other	0	2562	NDP	60206
ROSEMONT LA PETITE PATRIE	75	223	False	NDP	7697	LPC	4425	BQ	4291	GPC	1088	Other	0	17501	NDP	60206
SAANICH GULF ISLANDS	2	238	False	GPC	88	LPC	58	CPC	54	NDP	18	Other	0	218	GPC	68150
SAANICH GULF ISLANDS	35	238	False	GPC	2844	CPC	1245	LPC	1080	NDP	701	Other	0	5870	GPC	68150
SAINT HYACINTHE BAGOT	1	247	False	BQ	118	LPC	50	CPC	45	NDP	43	Other	0	256	BQ	55914
SAINT HYACINTHE BAGOT	55	247	False	BQ	4607	LPC	2363	NDP	1995	CPC	1708	Other	0	10673	BQ	55914
SAINT JEAN	80	256	False	BQ	12864	LPC	9097	CPC	3136	NDP	1952	Other	0	27049	BQ	61875
SAINT JOHN ROTHESAY	3	170	False	LPC	116	CPC	79	GPC	19	NDP	18	Other	0	232	LPC	41253
SAINT MAURICE CHAMPLAIN	5	281	False	LPC	238	BQ	144	CPC	55	PPC	14	Other	0	451	LPC	58414
SAINT MAURICE CHAMPLAIN	210	281	False	LPC	12930	BQ	11812	CPC	5629	NDP	1910	Other	0	32281	LPC	58414
SALABERRY SUROIT	90	286	False	BQ	13573	LPC	8830	CPC	2864	NDP	2126	Other	0	27393	BQ	62903
SHEFFORD	220	271	False	BQ	17216	LPC	16266	CPC	5348	NDP	2744	Other	0	41574	BQ	60913
SHEFFORD	268	271	False	BQ	22752	LPC	21647	CPC	7245	NDP	3559	Other	0	55203	BQ	60913
SHERBROOKE	95	261	False	LPC	4151	NDP	3607	BQ	3227	CPC	1307	Other	0	12292	LPC	59726
SHERBROOKE	145	261	False	LPC	6422	NDP	6210	BQ	5349	CPC	2056	Other	0	20037	LPC	59726
SHERBROOKE	204	261	False	NDP	10072	LPC	10014	BQ	8923	CPC	3462	Other	0	32471	LPC	59726
SHERBROOKE	220	261	False	LPC	11291	NDP	11105	BQ	9823	CPC	3830	Other	0	36049	LPC	59726
SHERBROOKE	255	261	False	LPC	15845	NDP	15338	BQ	14007	CPC	5689	Other	0	50879	LPC	59726
SOUTH SHORE ST. MARGARETS	5	260	False	CPC	170	LPC	153	NDP	52	GPC	25	Other	0	400	LPC	52518
SOUTH SHORE ST. MARGARETS	100	260	False	LPC	7974	CPC	5458	NDP	3081	GPC	2156	Other	0	18669	LPC	52518
ST. JOHN'S EST	1	182	False	NDP	50	CPC	41	LPC	29	GPC	1	Other	0	121	NDP	45072
ST. JOHN'S EST	15	182	False	NDP	1145	LPC	867	CPC	536	GPC	42	Other	0	2590	NDP	45072
ST. JOHN'S EST	50	182	False	NDP	4454	LPC	3148	CPC	1757	GPC	157	Other	0	9516	NDP	45072
ST. JOHN'S SUD MOUNT PEARL	29	185	False	LPC	2567	NDP	1650	CPC	786	GPC	90	Other	0	5093	LPC	40666
ST. JOHN'S SUD MOUNT PEARL	30	185	False	LPC	2816	NDP	1743	CPC	895	GPC	96	Other	0	5550	LPC	40666
SYDNEY VICTORIA	130	196	False	CPC	7193	LPC	7048	NDP	5053	Other	3962	Other	0	23256	LPC	40565
TOBIQUE MACTAQUAC	1	184	False	CPC	17	LPC	10	GPC	4	NDP	1	Other	0	32	CPC	38201
TOBIQUE MACTAQUAC	30	184	False	CPC	2273	LPC	819	GPC	460	NDP	261	Other	0	3813	CPC	38201
TORONTO CENTRE	95	257	False	LPC	7748	NDP	3261	CPC	1665	GPC	959	Other	0	13633	LPC	54512
TROIS RIVIERES	23	260	False	BQ	777	LPC	710	CPC	687	NDP	389	Other	0	2563	BQ	60538
TROIS RIVIERES	125	260	False	BQ	5083	LPC	4980	CPC	4624	NDP	2991	Other	0	17678	BQ	60538
TROIS RIVIERES	220	260	False	BQ	12871	LPC	12011	CPC	11554	NDP	7536	Other	0	43972	BQ	60538
UNIVERSITY ROSEDALE	27	207	False	LPC	2534	CPC	925	NDP	856	GPC	357	Other	0	4672	LPC	57391
VANCOUVER GRANVILLE	8	205	False	LPC	189	Other	116	NDP	98	CPC	85	Other	0	488	Ind	53032
VANCOUVER GRANVILLE	50	205	False	Other	1959	CPC	1942	LPC	1836	NDP	1086	Other	0	6823	Ind	53032
VANCOUVER GRANVILLE	77	205	False	Other	3300	CPC	3149	LPC	3025	NDP	1675	Other	0	11149	Ind	53032
VANCOUVER GRANVILLE	175	205	False	Other	9749	LPC	8361	CPC	7100	NDP	4646	Other	0	29856	Ind	53032
WINNIPEG CENTRE	85	175	False	GPC	8606	NDP	4976	LPC	4474	CPC	2435	Other	0	20491	NDP	31724