Text as Data: Computational Text Analysis

Week 4:
Supervised Machine Learning Technqiues

Ashrakat Elshehawy

Department of Politics and International Relations,
University of Oxford

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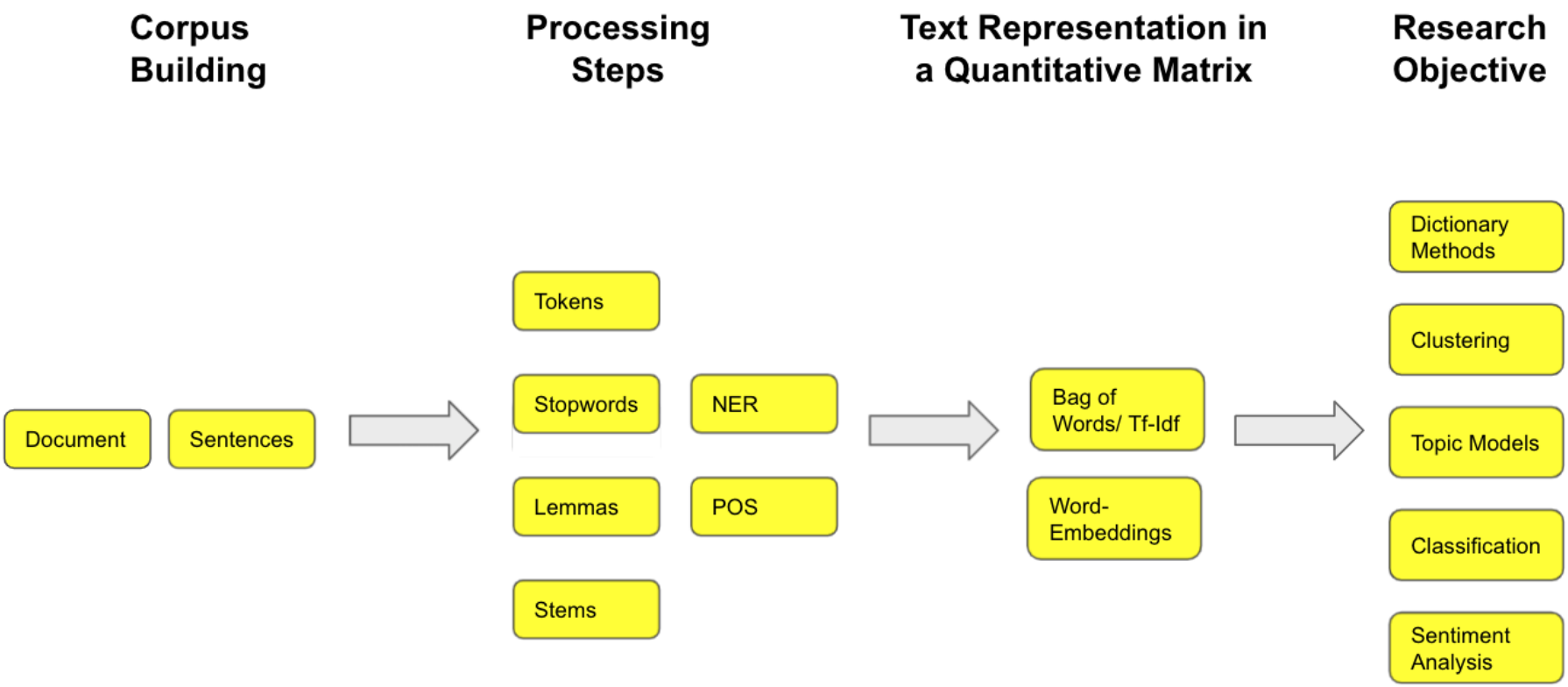
Overview from Text to Data[1]



[1] Slides for the session are based on Federico Nanni's course of Computational Text Analysis at U Mannheim

Recap - What have we learned until now?

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Supervised Machine Learning:

Classification as a Supervised Technique

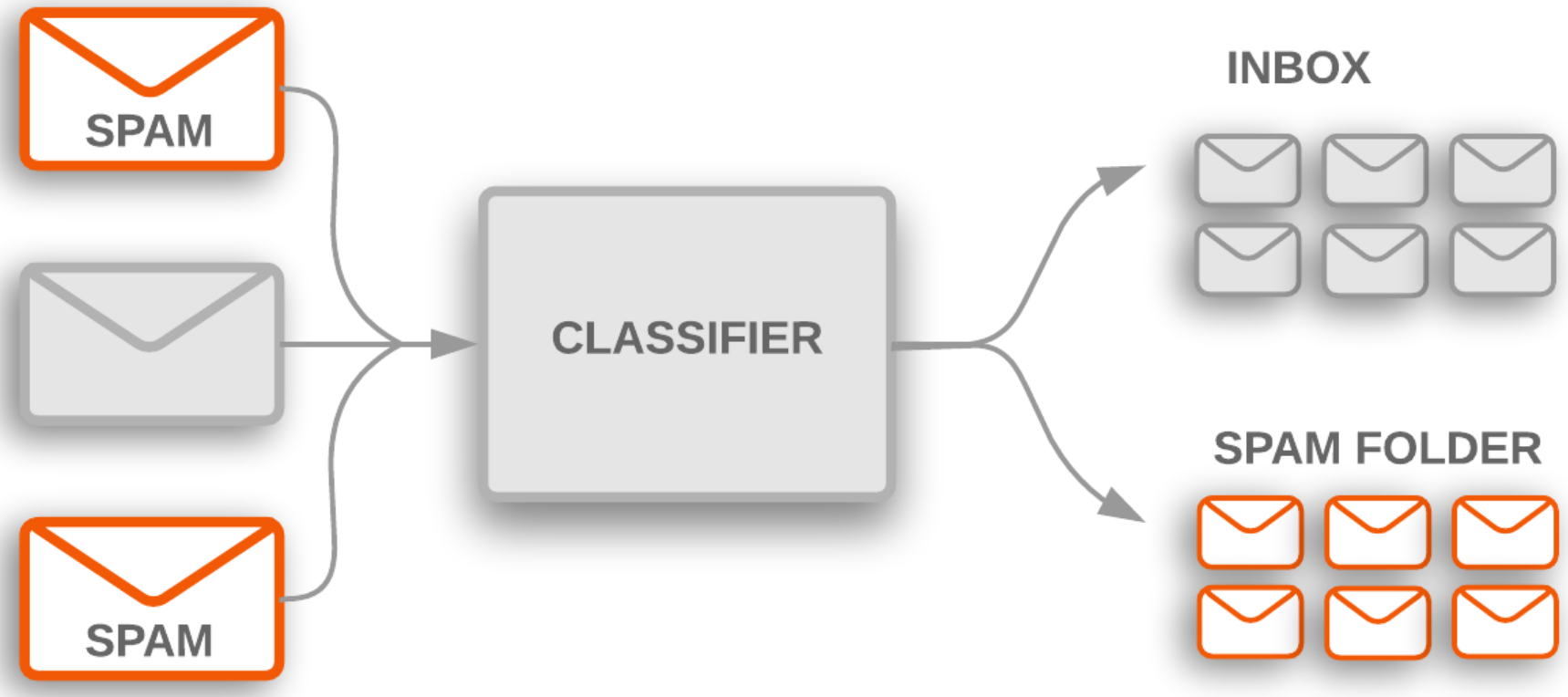

Image source: Source: Google Developers

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The task of associating instances (e.g., documents, sentences, words) with pre-defined labels

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- Topic Classification (multi-class)

Classification for Sentiment Analysis

This is a text classification task. It is often presented as a binary decision:

- for / against

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This is a text classification task. It is often presented as a binary decision:

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- good / bad

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Dictionaries could be used in both settings.

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- Defining rules is time consuming and inherently subjective

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Problems with Machine Learning

- Labeling is extremely time consuming and tedious
- Trained models are difficult to interpret
- Some algorithms work better on certain tasks (no free lunch theorem)

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→ A (properly) labelled dataset is called gold standard (or ground-truth

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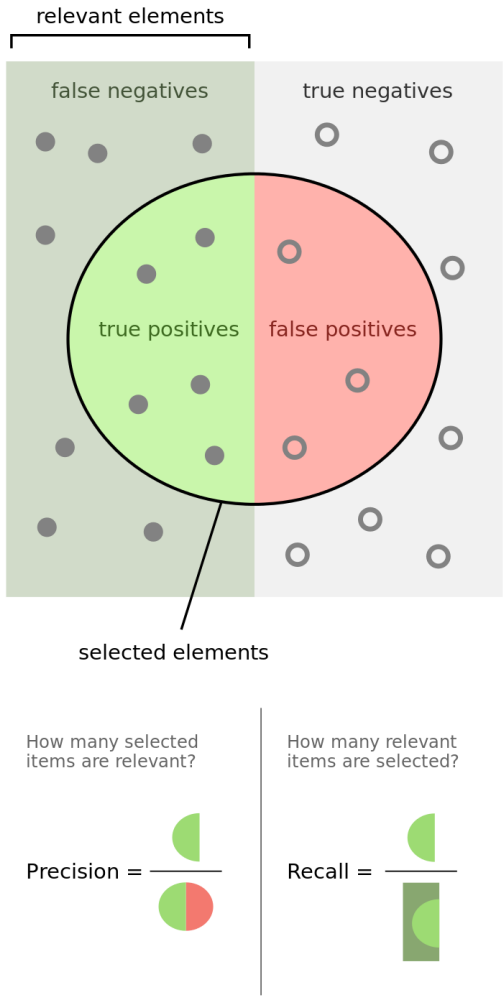
  - Negative: 93%, Positive: 22%

Classification: Precision and Recall

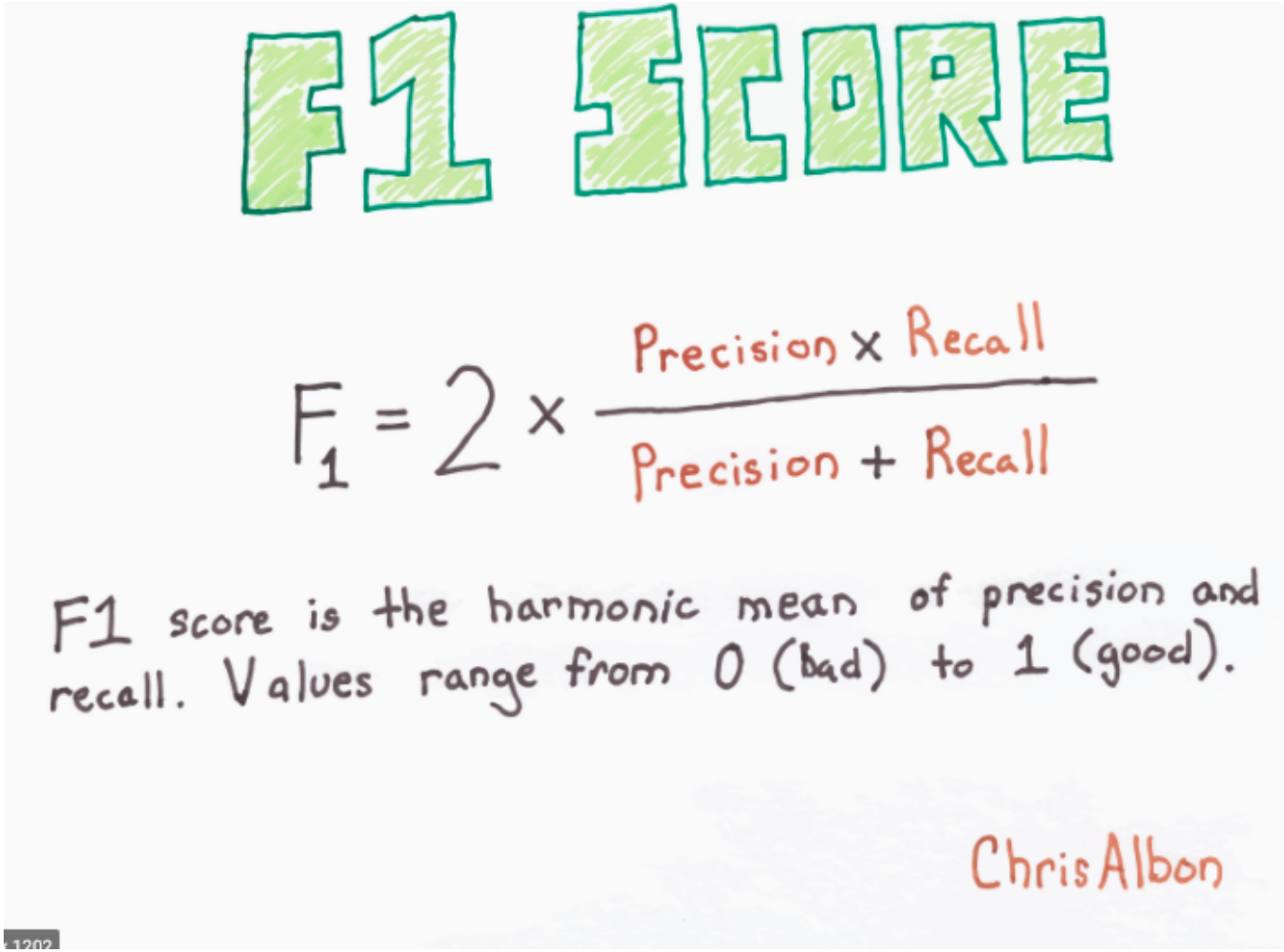
Precision: (true positives / all positives)

Recall: (true positives / relevant elements)



Source: Wikipedia

Classification: F1 score



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- You test on a different dataset (test set), to measure performances

Over-fitting and Under-fitting[2]

- Underfit Model is simple because of the assumptions made about the data pays very little attention to the training data and oversimplifies the model

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- Overfitting means your model is not Generalised. Algorithm used to build prediction model is very complex - it has over learned underlying patterns in training data

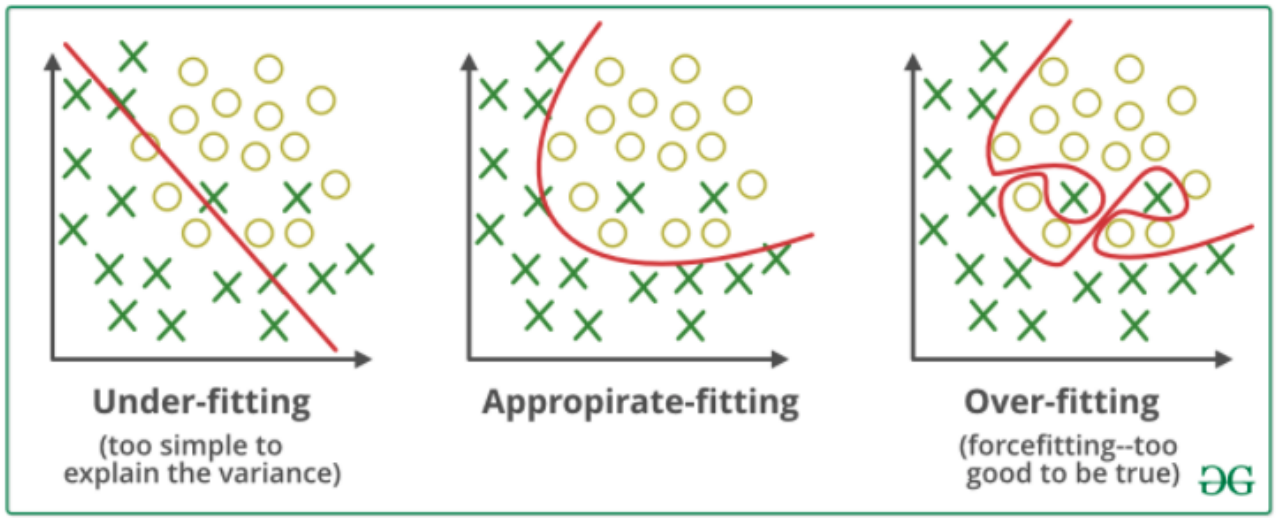

Figure: `https://www.geeksforgeeks.org/underfitting-and-overfitting-in-machine-learning/`

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Figure: Source:AnalyticsVidhya

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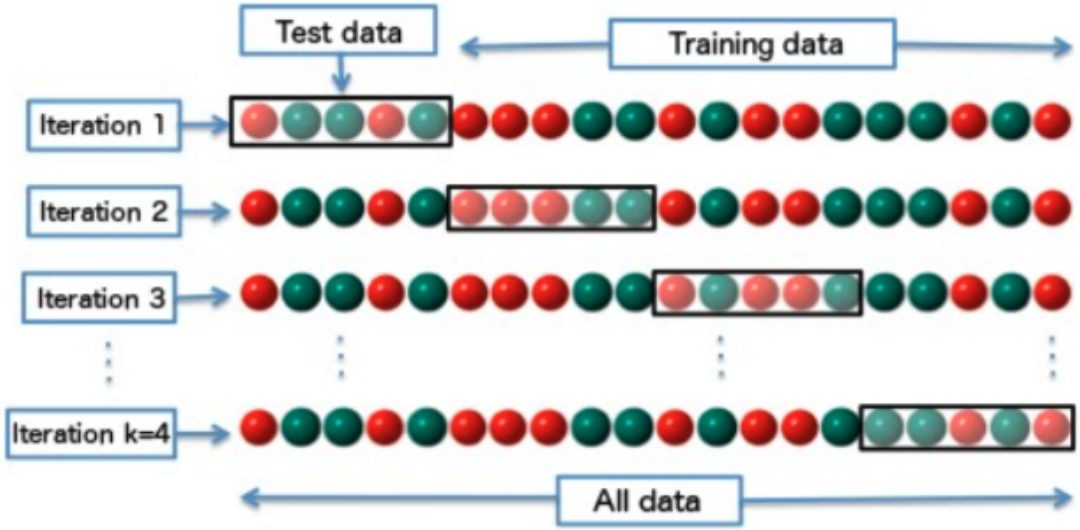

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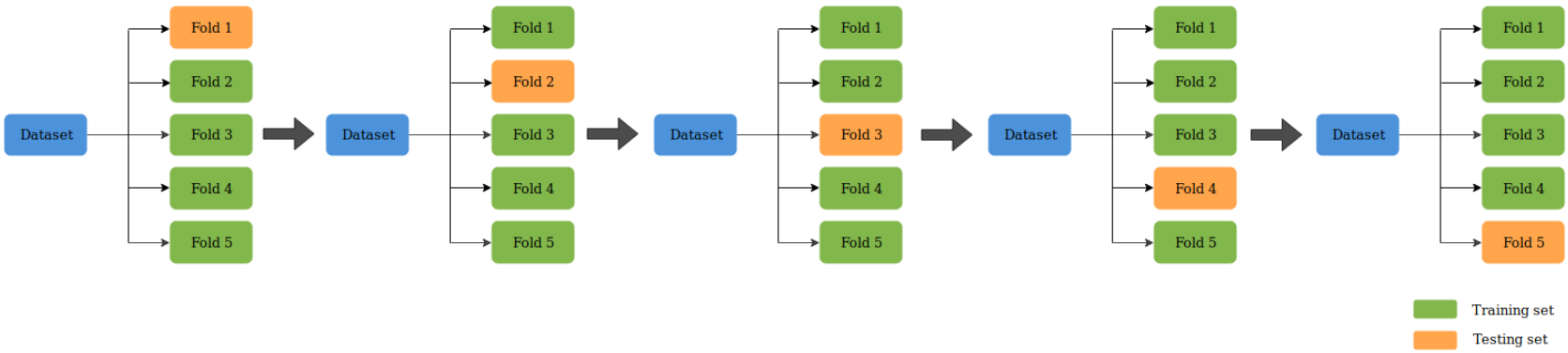

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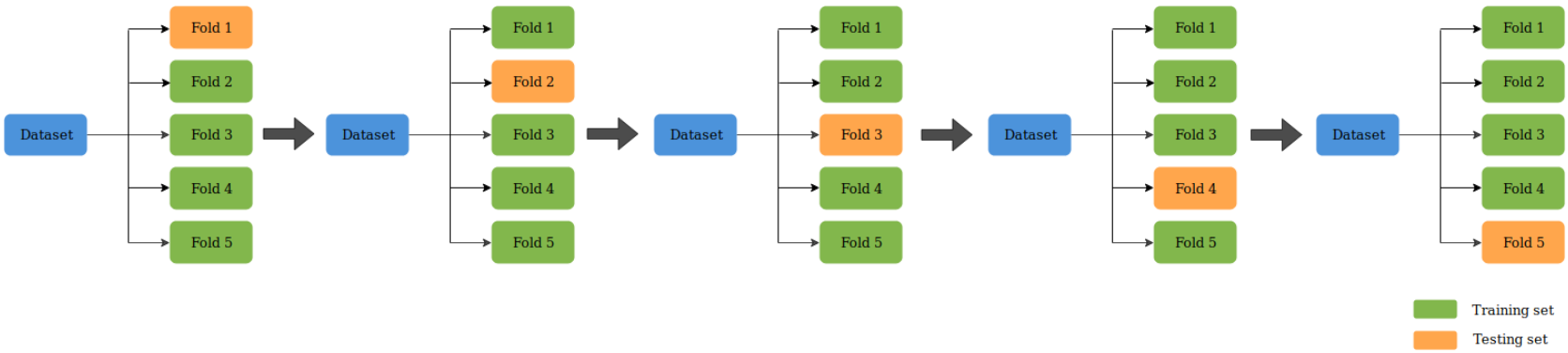

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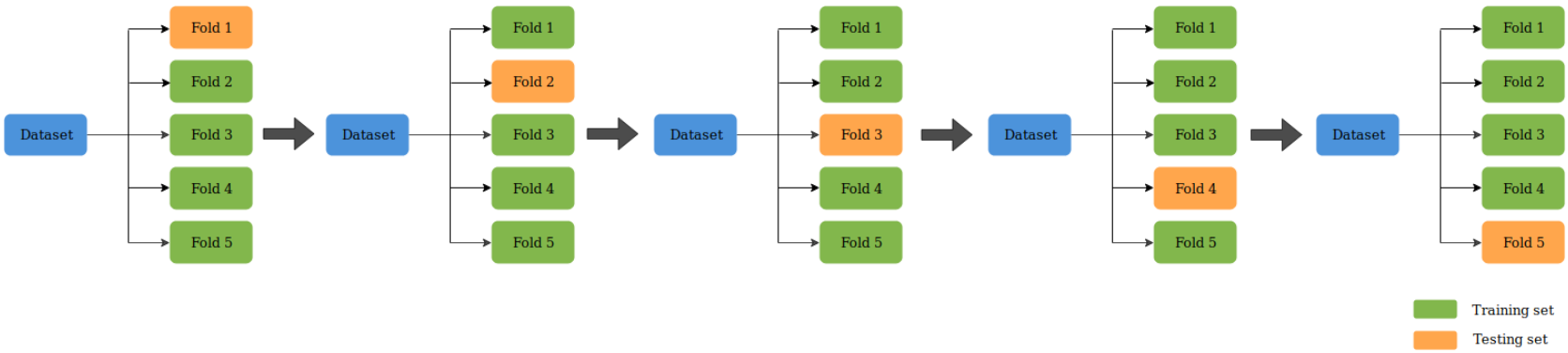

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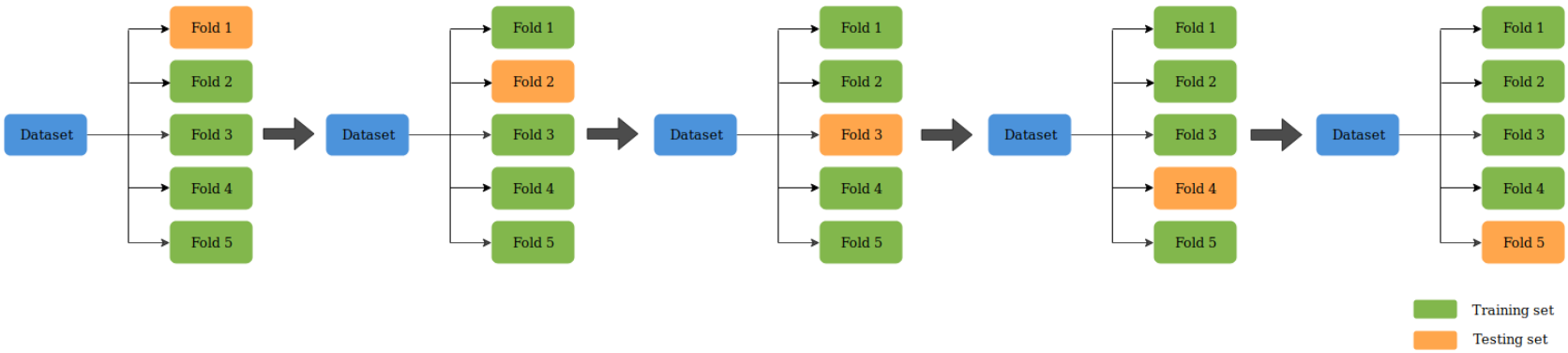

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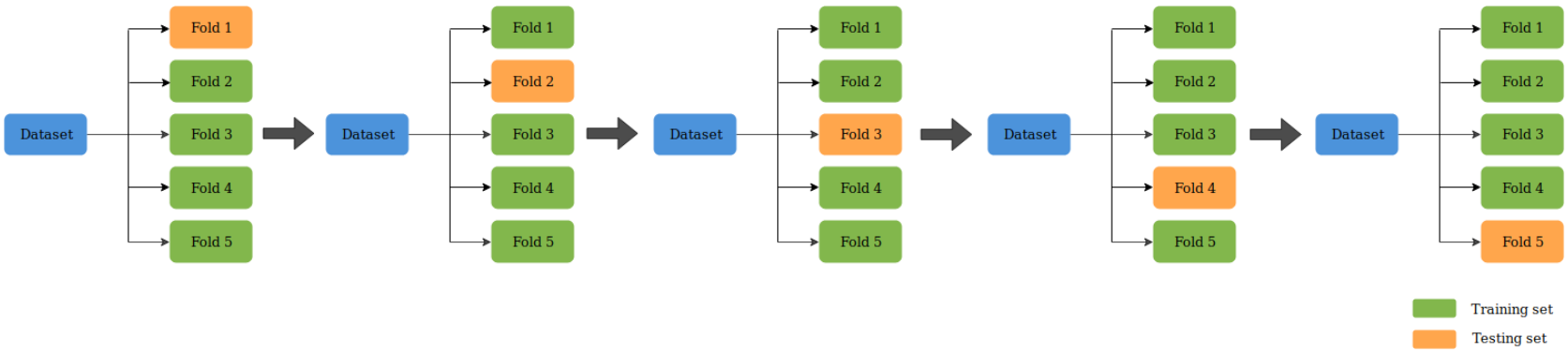

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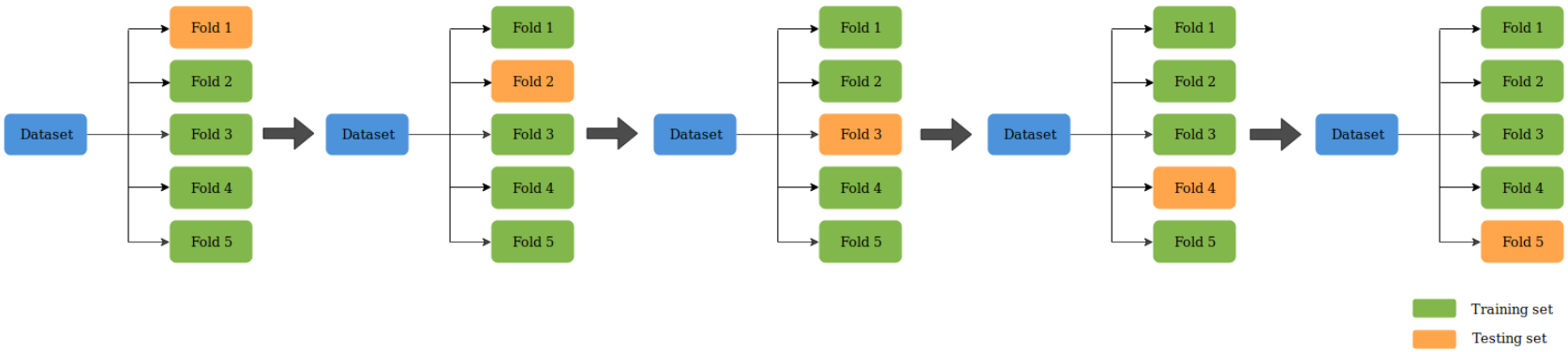

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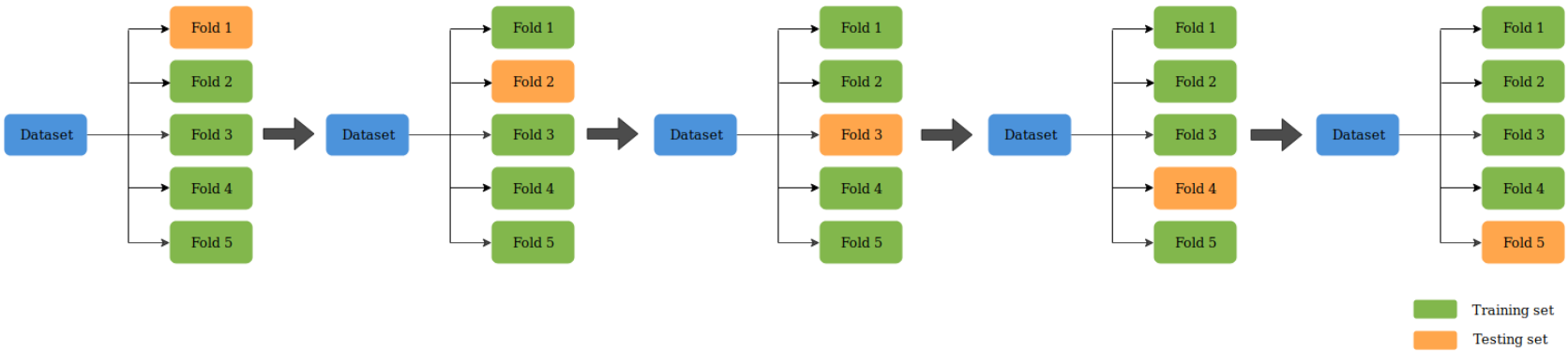

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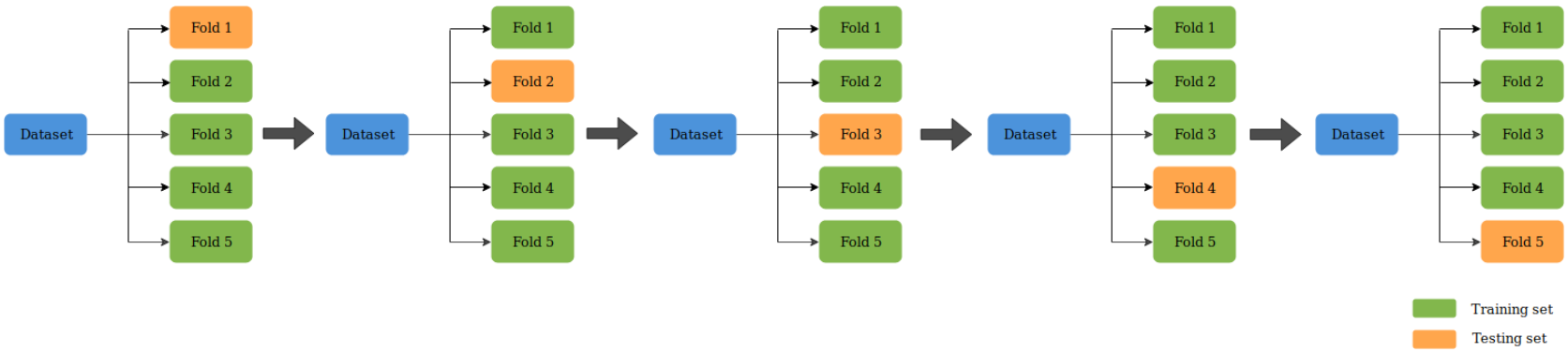

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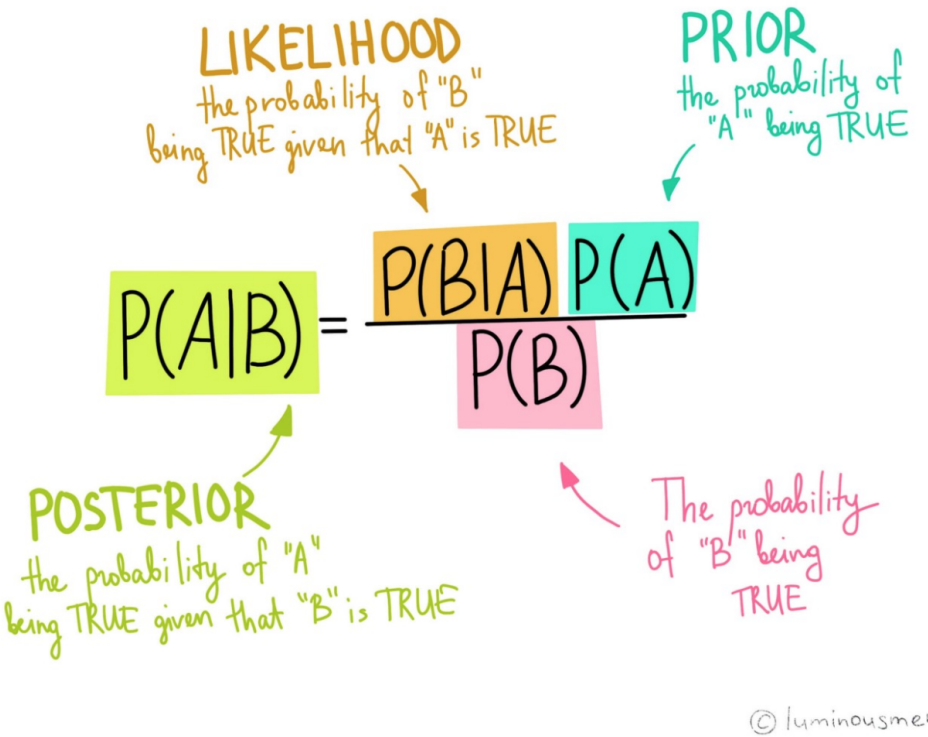
Naive Bayes Classifier

A probabilistic generative model: outputs are class/label probabilities.



$$P(\text{label} \mid \text{word}_1 \ldots \text{word}_n) = \frac{P(\text{word}_1 \ldots \text{word}_n \mid \text{label}) * P(\text{label})}{P(\text{word}_1 \ldots \text{word}_n)}$$

What you want to know

What you see

Computed on the training data

Compared to other labels

Computed on the training data

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Take away: Often used as a competitive baseline for text classification tasks

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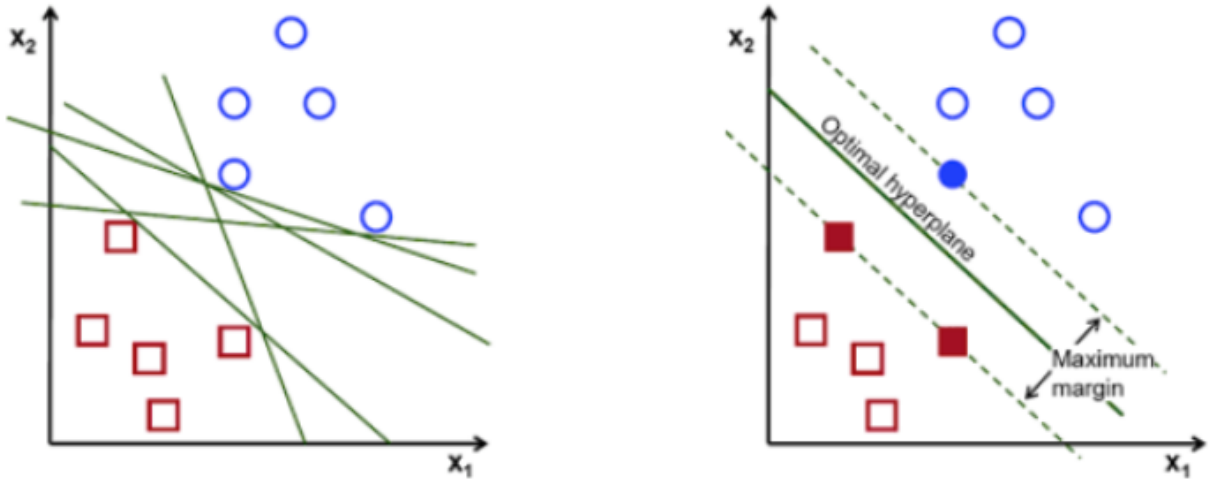

Figure: Source: towardsdatascience.com

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- Find hyperplane that maximizes margin between closest opposite examples.

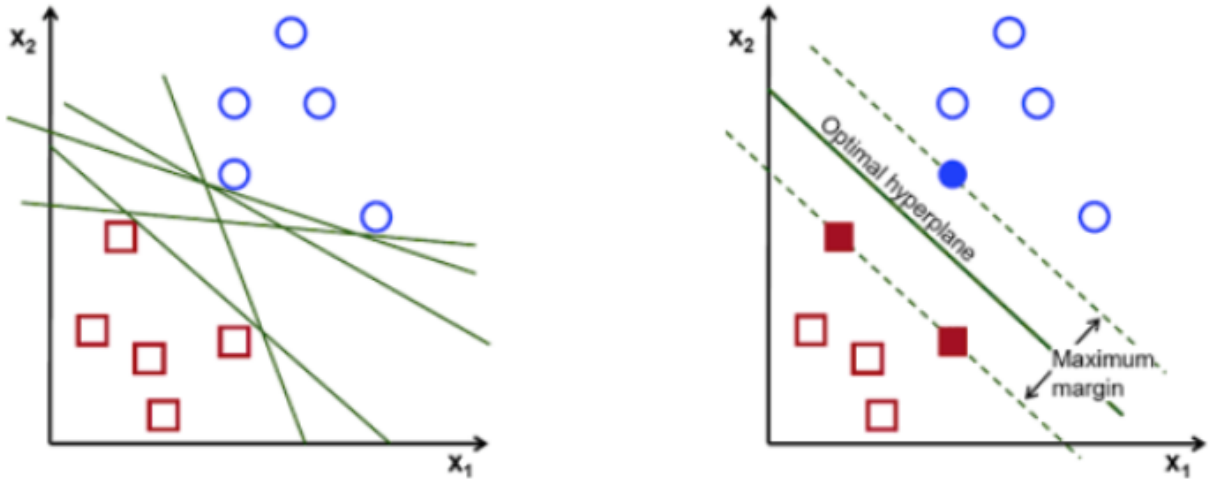
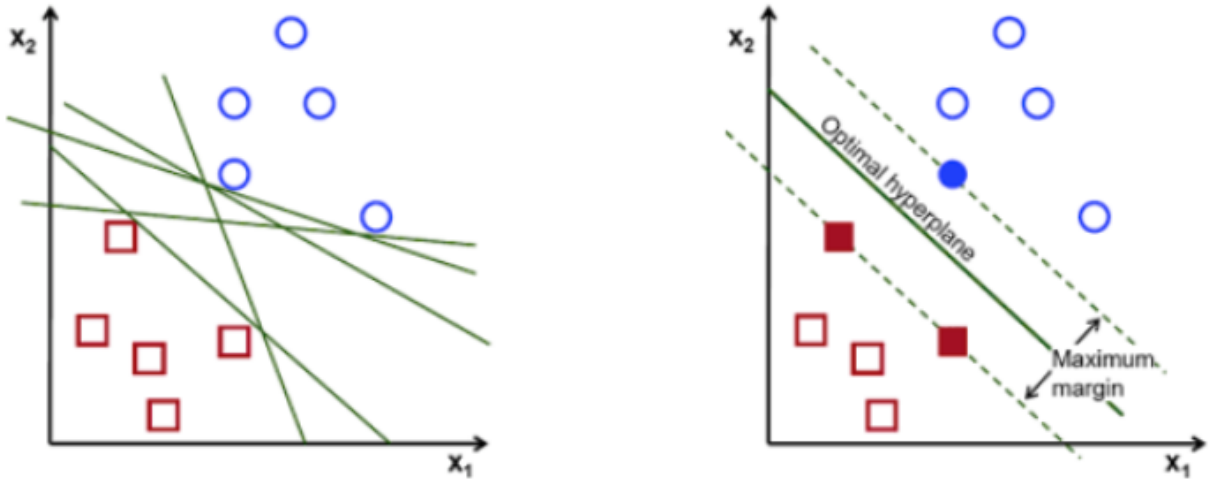


Figure: Source: towardsdatascience.com

Support Vector Machine (SVM) Classifier

Non-probabilistic discriminative model.

- Project instances in space.
- Find hyperplane that maximizes margin between closest opposite examples.



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- Kernel-trick = if no optimal hyperplane, maps examples to a higher-dim. space

Further on SVM

The parameter C determines how much you want to avoid misclassifying each training example.

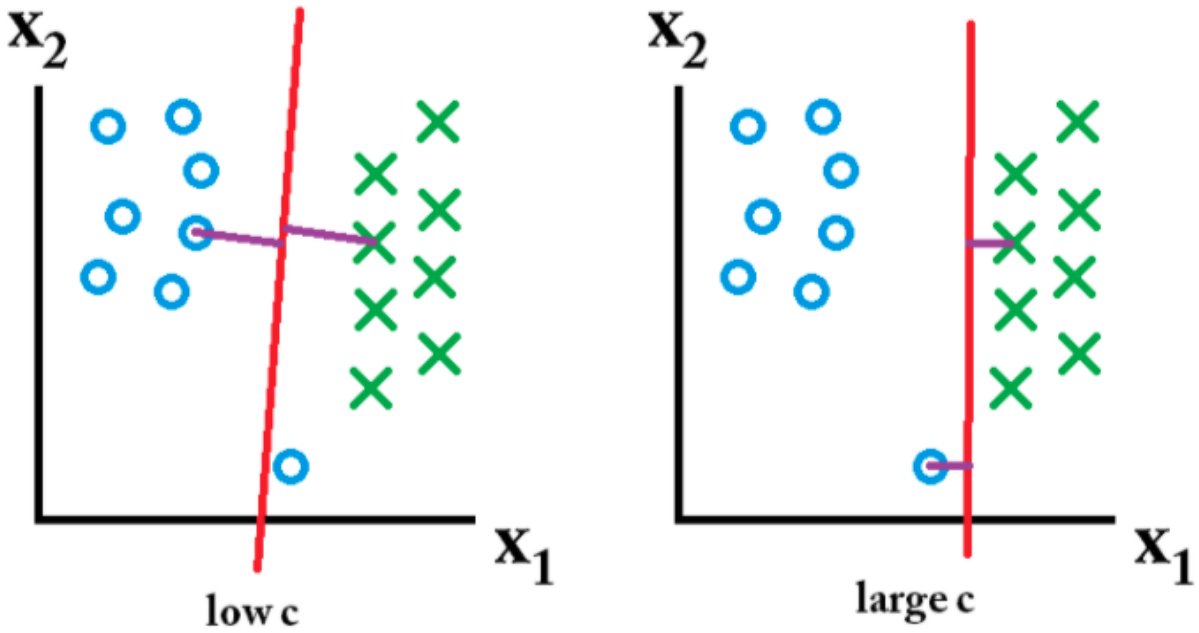

Figure: Source: From:https://stats.stackexchange.com/questions/31066/what-is-the-influence-of-c-in-svms-with-linear-kernel

SVM Pros and Cons

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