92586 Computational Linguistics

Lesson 9. Training and Evaluation in Machine Learning

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In part, derived from Appendix D of Lane et al. (2019)

Current Training and Evaluation Cycle

Current Training and Evaluation Cycle

This is what we have been doing so far

1. Train a model m on a dataset C
2. Apply the resulting model m to the same dataset C
3. Compute error or accuracy

This is wrong!

Generalisation

A model can generalize if it is able to correctly label an example that is **outside of the training set** (Lane et al., 2019, 447)

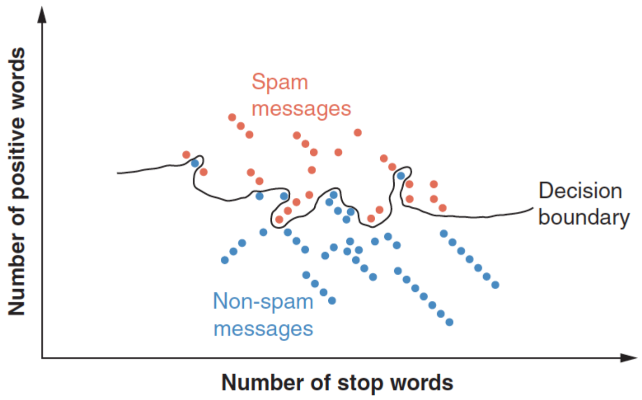
There are two big enemies of generalisation:

- Overfitting
- Underfitting

Overfitting

A model that predicts perfectly the training examples

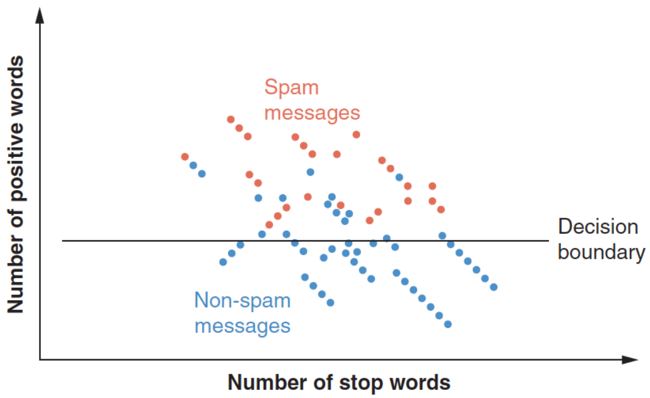
- It lacks capacity to discriminate new data
- In general you should not trust it (either your problem is trivial or your model/representations do no generalise)



Underfitting

A model that makes many mistakes, even on the training examples

- It lacks capacity to discriminate new data (as well!)
- In general you should not trust it (your problem is too difficult or your model/representations are not enough)



Fitting (Generalising)

A model that, even if it makes some mistakes, the training examples it makes about the same amount of mistakes on the testing examples

- It has the capacity to discriminate (generalise on) new data
- In general you can trust it (your problem is reasonable and your model/representations are good enough)

Data Partitioning

Data Partitioning

So far, we have used all the data for both training and testing

This is wrong!

Instead, we need to partition it by. . .

- Held out
- Cross-fit

Always shuffle the data first

Data Partitioning: held out

Fixing three data partitions: one specific purpose each

Training	Instances used to train the model
Development	Instances to optimise the model
Test	Instances to test the model

1: **while** performance on dev $<$ reasonable **do**
2: adjust configuration
3: train m on the training partition
4: evaluate the performance of m on the dev partition
5: re-train m on train+dev partition ▷ only once
6: evaluate the performance of m on the test partition

Data Partitioning: held out

Adjust configuration

- Adapt representation
- Change learning parameters
- Change learning model

Reasonable performance

- A pre-defined value is achieved (e.g., better than a reasonable baseline)
- The models has stopped improving (convergence)

Evaluate on Test

- Carried out only once, with the best model on development
- Keep the test aside (and don't look at it) during tuning

Data Partitioning: held out

Typical distribution

Mid-size data

training	70%
development	15%
testing	15%

Large data

training	90%
development	5%
testing	5%

Often, the partitions have been predefined by the people behind the data release. In general, just stick to that partition

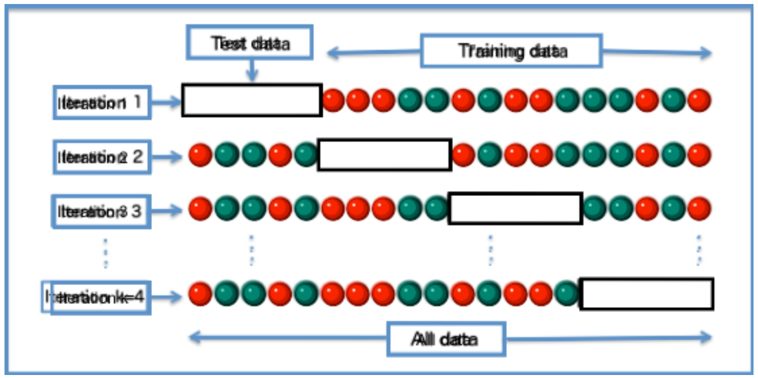
Data Partitioning: k-fold cross validation

Splitting into k folds which play different roles in different iterations

Fold 1 First $|C|/k$ instances
Fold 2 Next $|C|/k$ instances
...
Fold k Last $|C|/k$ instances

split C into k partitions
performance = {}
for i in $[1, 2, \ldots, k]$ **do**
  training set ← all partitions, except i
  validation set ← partition i
  train on the training set ▷ same as before
  perf = evaluate on the validation set
  performance[i] = perf
overall_performace = avg(performance)

Data Partitioning: k-fold cross validation



From `https://en.wikipedia.org/wiki/Cross-validation_(statistics)`

Data Partitioning: k-fold cross validation

Typical evaluating strategies

- Compute mean and standard deviation over the k experiments (sd is important: if it is too high, the model is to volatile, or the partitions are not representative)
- Train a new model on all folds, with the best configuration, and test on an extra test set

Data Partitioning: leave-one-out cross validation

An extreme case in which $k = |C|$

- Reasonable when the data is relatively small
- It might be too expensive

Imbalanced Data

Imbalanced Data: example

Imagine you want to train a model that differentiates dogs and cats (Lane et al., 2019, pp. 452–453)

dogs	200 pictures
cats	20,000 pictures

- A model predicting **always** "cat" will be correct 99% of the times
- Such model wont be able to predict any "dog"

Can you think of this kind of data in real life?

Dealing with Imbalanced Data

Oversampling
Repeating examples from the under-represented class(es)

Undersampling
Dropping examples from the over-represented class(es)

Data Augmentation
Produce new instances by perturbation of the existing ones or from scratch

Distant Supervision
Use some labeled training data to label unlabelled data, producing new (noisy) entries

Performance Metrics

Performance Metrics

True, false, positive, and negative

		true condition	
		positive	negative
predicted condition	positive	true positive	false positive
	negative	false negative	true positive

Performance Metrics

Accuracy

		true condition	
		positive	negative
predicted condition	positive	**true positive**	false positive
	negative	false negative	**true negative**

$$Acc = \frac{|\text{true positives}| + |\text{true negatives}|}{|\text{all instances}|} \tag{1}$$

Performance Metrics

Precision

		true condition	
		positive	negative
predicted condition	positive	**true positive**	**false positive**
	negative	false negative	true negative

$$P = \frac{|\text{true positives}|}{|\text{true positives}| + |\text{false positives}|} \tag{2}$$

Performance Metrics

Recall

		true condition	
		positive	negative
predicted	positive	**true positive**	false positive
condition	negative	**false negative**	true negative

$$R = \frac{|\text{true positives}|}{|\text{true positives}| + |\text{false negatives}|} \tag{3}$$

Performance Metrics

F_1-measure

		true condition	
		positive	negative
predicted	positive	true positive	false positive
condition	negative	false negative	true positive

Combining Eqs. (2) and (3):

$$F_1 = 2\frac{P \cdot R}{P + R} \tag{4}$$

Let us see

Performance Metrics

More on Evaluation

- If the problem is multi-class, the performance is computed on all the classes and combined
  - Micro-averaged
  - Macro-averaged
- If the problem is sequence tagging (e.g., plagiarism detection), the items are characters or words, not documents
- If the problem is not classification, but regression, we need **root mean square error**
- If the problem is $\sim$text generation (e.g., machine translation), we need other evaluation schema

Coming Next

- Back to LSA

References

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.