COMP4650/6490 Document Analysis

Evaluation in NLP

ANU School of Computing

Administrative matters

- Feedback survey 2
  - Opens: Monday, 16 October 2023, 11:00 AM
  - Closes: Monday, 23 October 2023, 5:00 PM
- Practice exercises
  - Will be released soon
- Drop-in sessions
  - 1pm - 2pm Friday 20 October
  - 1pm - 3pm Thursday 26 October
  - 1pm - 2pm Friday 27 October
  - Room 3.41, Level 3, Hanna Neumann Building #145

Outline

- General evaluation techniques
- Term overlap metrics
- What to compare

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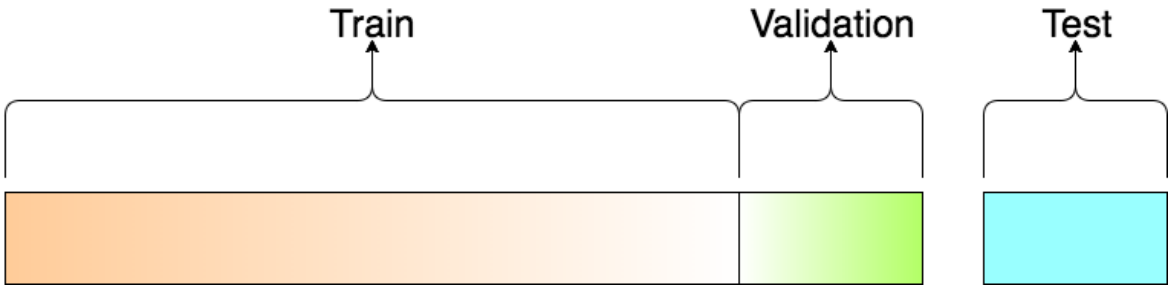
- Intrinsic evaluation
  Directly test a task correctness using a gold standard (also called ground truth), e.g.
  - Evaluate a POS-Tagger
  - Calculate the match between predicted and gold standard POS-tags

- Extrinsic evaluation
  Test whether the output is useful for downstream tasks, e.g.
  - Evaluate a summarisation technique in an IR setting
  - Does using summaries instead of complete documents help a particul ar retrieval task?

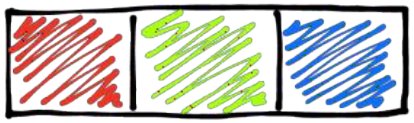
- NLP methods are usually intrinsically evaluated against a gold standard

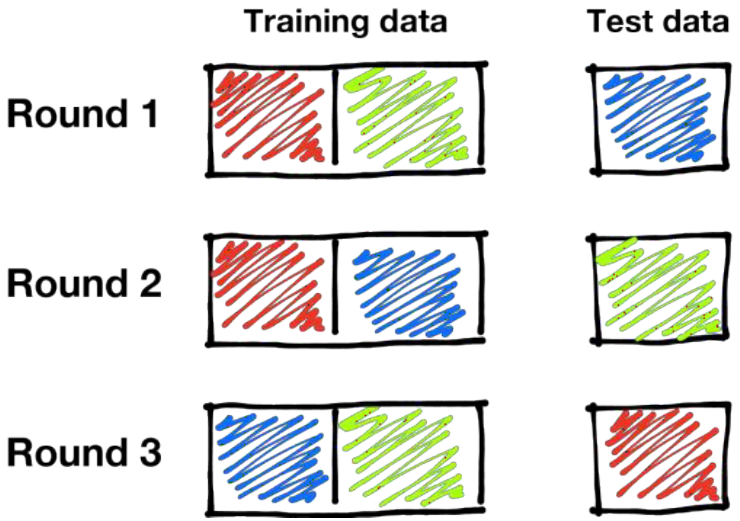
Evaluation methodology recap

- Always split your data in three sets:



- Never test with the training set
- With small data sets, use cross-validation





Classification metrics recap

- Accuracy
  - The number of correct predictions, divided by the total number of instances:

$$\text{accuracy}(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{1}{N}\sum_{i=1}^{N} \delta(y^{(i)} = \hat{y}^{(i)})$$

  - Not suitable for class-imbalance datasets, e.g.
    - Discover symptoms of a rare disease (positive class), which only appears in 1% of the dataset. If all instances are classified as negative the accuracy is 99%, but it's useless.
- Precision, Recall, F-measure
  - There are two possible errors (FP, FN), and two ways to be correct (TP, TN)
    - False positive (FP): the system incorrectly predicts the label
    - False negative (FN): the system incorrectly fails to predict the label
    - True positive (TP): the system correctly predicts the label
    - True negative (TN): the system correctly predicts that the label does not apply to this instance

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad \text{F}_\alpha = \frac{1}{\frac{\alpha}{\text{Precision}} + \frac{1-\alpha}{\text{Recall}}}, \quad \alpha \in [0,1]$$

Evaluating multi-class classification

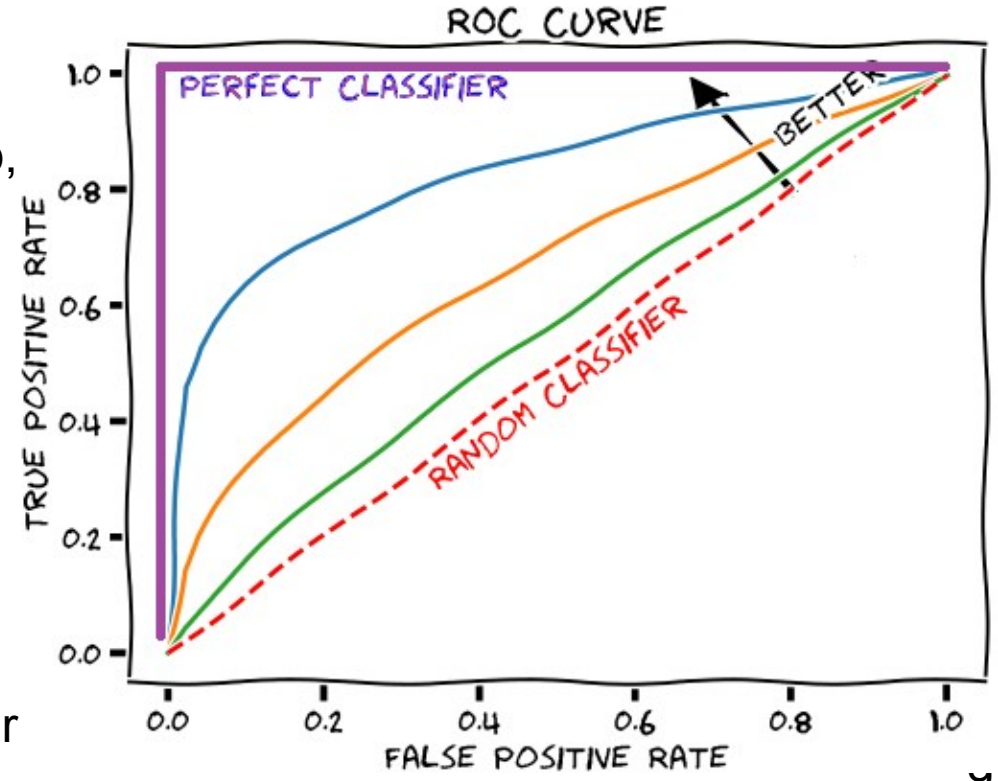
- Macro F-measure:
  When there are multiple labels of interest (e.g. in word sense disambiguation), it is necessary to combine the F-measure across each class.

$$\text{Macro-F}_\alpha(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{1}{K} \sum_{k=1}^{K} \text{F}_\alpha(y_k, \hat{y}_k)$$

- Micro F-measure:
  Counting the total true positives, false negatives and false positives globally, then calculate the F-measure

Threshold free metric: ROC-AUC

- AUC: Area Under The Curve
- ROC: Receiver Operating Characteristics
- For binary classification, it allows to tradeoff between Precision and Recall
  - FPR = FP / (FP + TN)
  - TPR = TP / (TP + FN)
  - AUROC of 0.5 (area under the red dashed line) corresponds to a coin flip, i.e. a random model
  - AUROC less than 0.7 is usually sub-optimal performance
  - AUROC of 0.70 to 0.80 is often good performance
  - AUROC greater than 0.8 is often excellent performance
  - AUROC of 1.0 (area under the purple line) corresponds to a perfect classifier



Examples of evaluation in NLP tasks

- Semantic parsing
  - Accuracy
  - A logical formula is correct or not, an SQL is correct or not. No partially correct cases
- Dependency parsing
  - Precision and Recall of UAS or LAS
  - Unlabelled attachment score (UAS)
    - Evaluates the tree structure
    - Proportion of words whose head is correctly assigned
  - Labelled attachment score (LAS)
    - Evaluates the tree and the arcs relations
    - Proportion of words whose head is correctly assigned with the right dependency label
- Named entity recognition
  - Macro Precision/Recall (as with many other multi-class classification problems)
- Ranking (e.g. Coreference resolution)
  - Mean Average Precision
  - Mean Reciprocal Rank

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When the output is a text sequence

The output could be a text sequence

- Machine translation
- Text generation
- Text simplification
- Image Caption Generation

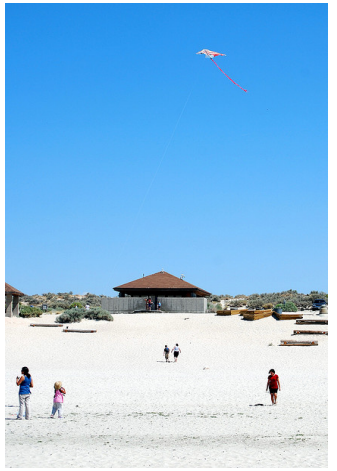
Challenges:

- Almost infinite possible correct outputs
- Unlikely that the model will give the same result as a human labeller
- Getting people to manually evaluate every output is costly

When the output is a text sequence

- Consider image captioning where the task is to generate a caption that describes an image:
  - The input is an image, the output is a sentence
  - Each image in the test set has multiple human written captions
  - We want to compare a generated caption to see how closely it matches the references

Ref1: A cat laying on a couch beside a remote.
Ref2: A cat sitting on the couch.
Ref3: A cat lounging on the couch next to a remote.



Ref1: Children flying a kite at the beach.
Ref2: Some children with a kite at the beach.
Ref3: A kite in the sky with some people beneath.

- The same sort of evaluation setting is used in tasks such as machine translation. (Though the input is a sequence of text rather than an image)
- Note: we don't always have multiple references, sometimes only one is available.

Term overlap evaluation metrics

Use term overlap metrics to evaluate:

- Machine translation
- Text summarisation
- Text simplification
- Q & A
- Chatbots
- Caption generation
- …

Popular term overlap metrics:

- BLEU
- ROUGE
- …

Term overlap evaluation metrics

BLEU (bilingual evaluation understudy)

- A modified form of precision to compare a candidate translation against multiple reference translations.
- Perfect match = 1.0, Perfect mismatch = 0.0
- Precision-based metrics are biased in favour of short translations → brevity penalty (BP)

$$p_n = \frac{\text{number of } n\text{-grams appearing in both reference and hypothesis translations}}{\text{number of } n\text{-grams appearing in the hypothesis translation}}.$$

- BLEU is based on $\exp \frac{1}{N} \sum_{n=1}^{N} \log p_n$ (usually with smoothing to avoid log(0))

Example:

- A reference translation and three system outputs
- For each output, p_n indicates the precision at each n-gram, BP indicates the brevity penalty.

	Translation	p_1	p_2	p_3	p_4	BP	BLEU
Reference	*Vinay likes programming in Python*						
Sys1	*To Vinay it like to program Python*	$\frac{2}{7}$	0	0	0	1	.0
Sys2	*Vinay likes Python*	$\frac{3}{3}$	$\frac{1}{2}$	0	0	.51	.0
Sys3	*Vinay likes programming in his pajamas*	$\frac{4}{6}$	$\frac{3}{5}$	$\frac{2}{4}$	$\frac{1}{3}$	1	.51

(no smoothing)

Term overlap evaluation metrics

- ROUGE (Recall-Oriented Understudy for Gisting Evaluation)
  - Calculate the recall between human and automatic outputs in terms of n-grams (n-gram overlap)
  - ROUGE-N: Overlap of n-grams between the system and a gold standard reference
  - Often, we use both BLEU and ROUGE.
  - ROUGE is used instead of BLEU in summarisation and text simplification tasks because getting high precision is easy (e.g. in summarisation just copy the first sentence verbatim)

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Classifier comparison

- Comparison between algorithms, e.g.
  - Logistic regressions vs. MLP
  - L2 regularisation vs. L1 regularisation
- Comparison between feature sets, e.g.
  - Bag-of-words vs. Word embeddings
  - Word embeddings vs. Character embeddings

Baselines

- How can we know if our result is good?
- Evaluate against a set of baselines:
  - trivial models (e.g. always predict most common class, random guessing)
  - simple models (e.g. logistic regression)
  - well known methods for your task
  - the current state of the art method

	BLEU-4	ROUGE
(1) Biten (Avg + CtxIns) [3]	0.89	12.2
(2) Biten (TBB + AttIns) [3]	0.76	12.2
(3) LSTM + GloVe + IA	1.97	13.6
(4) Transformer + GloVe + IA	3.48	17.0
(5) LSTM + RoBERTa + IA	3.45	17.0

Use multiple different evaluation metrics.

Example from (Tran et al. 2020) https://arxiv.org/abs/2004.08070

Ablation studies

- How do we prove that all parts of the proposed model are necessary?
- Ablation testing involves systematically removing (ablating) various aspects of a model, such as feature groups, to see if the ablated classifier is as good as the full model

	BLEU-4	ROUGE
(6) Transformer + RoBERTa	4.60	18.6
(7) + image attention	5.45	20.7
(8) + weighted RoBERTa	6.0	21.2
(9) + face attention	**6.05**	**21.4**
(10) + object attention	**6.05**	**21.4**

Example from (Tran et al. 2020) https://arxiv.org/abs/2004.08070

Different datasets

- How do we prove that our model is generally applicable to a problem not just a single dataset?
- Test on multiple different datasets
- Make sure to include any standard benchmark datasets

	NER				
	de	de_{06}	en	es	nl
Baevski et al. (2019)	-	-	93.5	-	-
Straková et al. (2019)	85.1	-	93.4	88.8	92.7
Yu et al. (2020)	86.4	90.3	93.5	90.3	93.7
Yamada et al. (2020)	-	-	94.3	-	-
XLM-R+Fine-tune	87.7	91.4	94.1	89.3	95.3
ACE+Fine-tune	**88.3**	**91.7**	**94.6**	**95.9**	**95.7**

Example from (Wang et al. 2020) https://arxiv.org/pdf/2010.05006.pdf

Summary

- General evaluation techniques
- Term overlap metrics
- What to compare

References

- Chapter 13. Speech and Language Processing (3rd ed. draft)
- Chapter 18. Natural language processing (by Jacob Eisenstein). 2018.
- Wang, Xinyu, et al. "Automated Concatenation of Embeddings for Structured Prediction." Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing. 2021.
- Tran, Alasdair, Alexander Mathews, and Lexing Xie. "Transform and tell: Entity-aware news image captioning." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.