BERT

Measuring Performance

Learning goals

- Task-specific metrics
- Metrics for text output
- How to evaluate retrieval
- Subtle aspects of evaluation

TASK-SPECIFIC EVALUATION: CLASSIFICATION

(Binary) Document-level Classification

- Accuracy
- Recall / Precision
- F1-Score
- ROC-Curve / AUC
- ...

(Multi-Class) Document-level classification

- Micro- / Macro-averaged F1
- Class-specific accuracies
- ...

TASK-SPECIFIC EVALUATION: RANKING (1)

Ranking:

- Use Cases:
  - Retrieval systems output a ranking of relevant documents
  - Search engines return top *k* results
  - ...
- Ranking evaluation metrics
  - Mean average precision (MAP)
  - Mean reciprocal rank (MRR)
  - Precision@k / Recall@k
  - ...

TASK-SPECIFIC EVALUATION: RANKING (2)

MAP:

$$AP@k = \frac{1}{r}\sum_{i=1}^{k} precision@i \cdot R_i$$

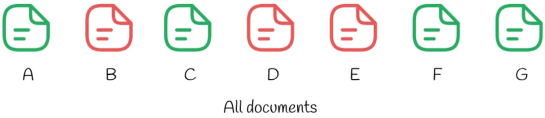
$$r = \text{number of relevant items}$$

$$R_i = \begin{cases} 1, & \text{if document } i \text{ is relevant} \\ 0, & \text{if document } i \text{ is not relevant} \end{cases}$$

▸ Source: towardsdatascience

TASK-SPECIFIC EVALUATION: RANKING (3)

Example MAP:



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TASK-SPECIFIC EVALUATION: RANKING (4)

Example MAP:

Retrieved documents for query Q_1

$$AP@5 = \frac{1}{3}\left(\frac{1}{1} + \frac{2}{3} + \frac{3}{4}\right) = 0.81$$

k	precision@k
1	$\frac{1}{1}$
2	$\frac{1}{2}$
3	$\frac{2}{3}$
4	$\frac{3}{4}$
5	$\frac{3}{5}$

▸ Source: towardsdatascience

TASK-SPECIFIC EVALUATION: RANKING (5)

Example MAP:

Retrieved documents for query Q_2

$$AP@5 = \frac{1}{3}\left(\frac{1}{2} + \frac{2}{4} + \frac{3}{5}\right) = 0.53$$

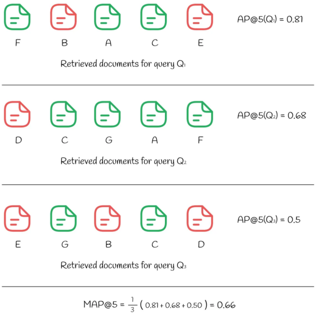
k	precision@k
1	$\frac{0}{1}$
2	$\frac{1}{2}$
3	$\frac{1}{3}$
4	$\frac{2}{4}$
5	$\frac{3}{5}$

Source: towardsdatascience

TASK-SPECIFIC EVALUATION: RANKING (6)

MAP:

$$MAP = \frac{1}{|Q|} \sum_{q \in Q} Ap_q@k, \;\; \textit{with } Q = \text{set of queries}$$



▸ Source: towardsdatascience

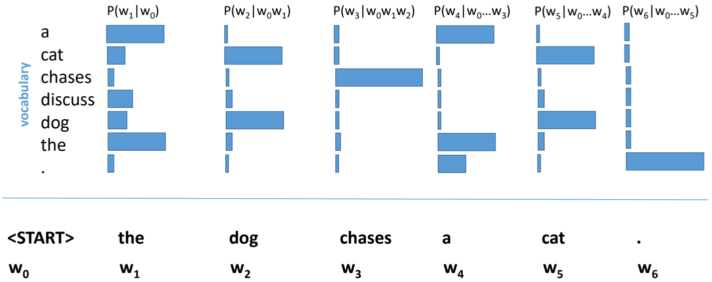
TASK-SPECIFIC EVALUATION: RANKING (7)

MRR:

$$RR = \frac{1}{\text{rank of first relevant item}}$$

$$MRR = \frac{1}{|Q|} \sum_{q \in Q} RR_q, \;\; with\ Q = \text{set of queries}$$

ARLMS



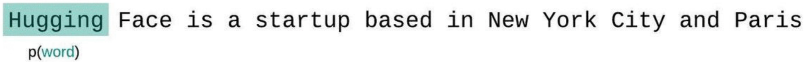
- **Question:** How can we measure “performance“ on this task?

ARLM PERPLEXITY (1)

- Natural choice for evaluating generated text
- Well-defined for ARLMs; trickier for MLMs
- Intuitively: *Amount of the model's surprisal when confronted with a sequence* (higher value means higher "surprisal")
- More technically: Measure of uncertainty of a probabilistic model
- Example: Perplexity of a fair k-sided die (uniform distribution) is k

ARLM PERPLEXITY (2)

- Autoregressive factorization of the sequence:



Source: huggingface

- Log-probability of i-th token given context: $\log(p_\theta(w_i|w_{<i}))$
  more “certain“ model $\rightarrow$ higher log-probability
- Aggregate[1] over the whole sequence:

$$PPL = \exp\left(-\frac{1}{t}\sum_{i=1}^{t}\log(p_\theta(w_i|w_{<i}))\right)$$

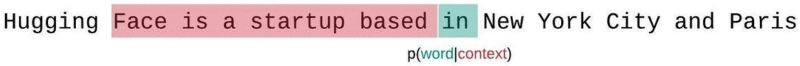
[1] The choice of the log’s base is basically arbitrary.

ARLM PERPLEXITY (3)

- *Lower bound* is **1**, i.e. the model predicts *every* token correctly (with a certainty of 100%)
- **Question:** Is this really desirable?
- *Upper bound* is $|V|$, i.e. the model only provides a random guess for every token with a probability of $\frac{1}{|V|}$
- Selection of state-of-the-art perplexities:
  - **1B Word Benchmark** ‣ Chelba et al., 2013 $(|V| = 800k)$
    PPL = 21,8 ‣ Dai et al., 2019
  - **WikiText-103** ‣ Merity et al., 2016 ($|V|$ = 270k)
    PPL = 10,8 ‣ Shoeybi et al., 2019
  - **Penn Treebank** ‣ Marcus et al., 1994 $(|V| = 10k)$
    PPL = 20,5 ‣ Brown et al., 2020

ARLM PERPLEXITY (4)

- *Problem:* Fixed context size of models (e.g. 1024 for GPT-2)



Source: huggingface

- *Possible solution:* Sliding window strategy
- Close approximation to “true“ autoregressive decomposition
- *Drawback:* Computationally expensive (individual forward pass for each token)

ARLM PERPLEXITY (5)

Question:

Is a language model with lower perplexity always a “better“ model?

Some (Dis)Advantages of perplexity:

- **Pro:** Straight-forward applicable
- **Pro:** Does not depend on “external“ labels
- **Con:** Not clear what value can be considered “good“
- **Con:** Corpus-/language-specific measure

EVALUATING GENERATED TEXT (1)

- **Question:** How else can we evaluate the quality of generated text?
- *Use cases:*
  - Machine translation
  - Question answering (extractive or abstractive)
  - Dialogue generation
  - Text summarization
  - Image Captioning
  - Code generation

EVALUATING GENERATED TEXT (2)

Machine Translation

- Metrics based on N-gram-overlap
  - BLEU (cf. Chap. 3.1) ▸ Papineni et al., 2002
  - ROUGE ▸ Lin, 2004
  - METEOR ▸ Banerjee and Lavie, 2005
- Metrics based pre-trained (neural) models
  - BertScore ▸ Zhang et al., 2019
  - BLEURT ▸ Sellam et al., 2020
  - COMET ▸ Rei et al., 2020

EVALUATING GENERATED TEXT (3)

- BLEU, ROUGE, METEOR:
  - "Bilingual evaluation understudy", originally for machine translation
  - Measures overlap of words, and longer word sequences of different sizes
  - BLEU: unreliable per-example, but correlates with human judgments on an aggregate level ▸ Reiter, 2018

EVALUATING GENERATED TEXT (3)

- BERTScore
  - Based on pre-trained BERT model
  - Also able to consider contextual similarities
  - Correlates better with human judgements
- BLEURT
  - Better per-example quality estimation by fine-tuning on examples with judgements
  - But: potential bias if tested systems are very different than training examples

EVALUATING GENERATED TEXT (4)

Question Answering / Summarization / Dialogues

- Aspects to consider
  - Factual correctness
  - Fluency
  - Stylistic aspects
  - Engagement
  - ...
- Human evaluation?! (cf. next slide)

HUMAN EVALUATOIN

Pros

- Possible where simply using metrics fails (esp. generated texts)
- Probably gold standard (given trained human evaluator)
- *Strong* learning signal for models (cf. RLHF, chapter 9)
- ...

Pros

- Manual, tedious work
- Costs and working conditions
- Subjectiveness
- Ambiguity
- ...