A Practical Introduction to Machine Learning in Python
Day 5 – Friday
»Next steps«

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Gesis

This part: State of the art and next steps

- Hot and happening: Transformers
  - Do I need all this fancy stuff?
- Your takeaway

Hot and happening: Transformers

The idea

BERT: Bidirectional Encoder Representations from Transformers (Devlin et al., 2019)

- (Huge) pre-trained model (by, e.g., Google) that is fine-tuned for specific task (by you)
- In simple neural networks, identical words have identical meanings – but meaning can depend on context
- Therefore, the model should take context into accounts. For example, in LSRTM we use *sequences* of words.
- But meaning of a word does not necessarily depend *sequentially* on the preceeding words in that order
- Solution: *Learn* which tokens *to attend to* (attention)

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- We can use BERT for a lot of different tasks: for sequence-to-sequence predictions (e.g., translation), but also for classification (yeah!)
- Can be done in keras
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Let's look at an example (imdb.ipynb)

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Things to consider

How important is. . .

- precision/recall? Am I satisfied with .88 when .90 is theoretically possible? .85? .80? .75?
- explainability?
- computational ressources?
- generalizability and out-of-sample performance?

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- Always estimate a simple baseline model first
- Invest in good hyperparameter-tuning (cross-validation, gridsearch) and don't forget to set aside unseen data for the *final* evaluation.
- If you (a) need to get the highest possible accuracy, or (b) have reasons to assume that the model does not generalize well enough (overfitting problems, bad out-of-sample prediction (e.g., training topics on newspaper 1, predicting topics in newspaper 2)), try embedding-based approaches, transformers, etc.
- Rule of thumb: the more abstract/latent what you want to predict, the less likely classic ML is going to work

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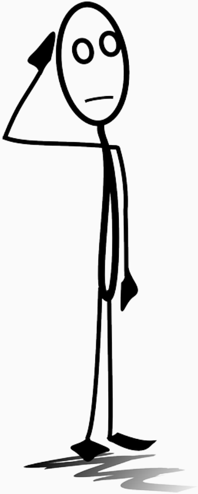
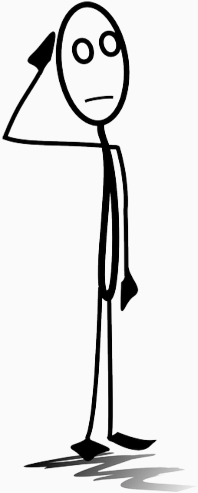
Your takeaway

(short recap of course)



Have your plans about how to and wether to use ML changed?



What are your next steps?

Last part: we help you working on (or discussing about) your own projects.

References

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Naacl hlt 2019 - 2019 conference of the north american chapter of the association for computational linguistics: Human language technologies - proceedings of the conference*.