Preliminary Pruning on Language Models for Code

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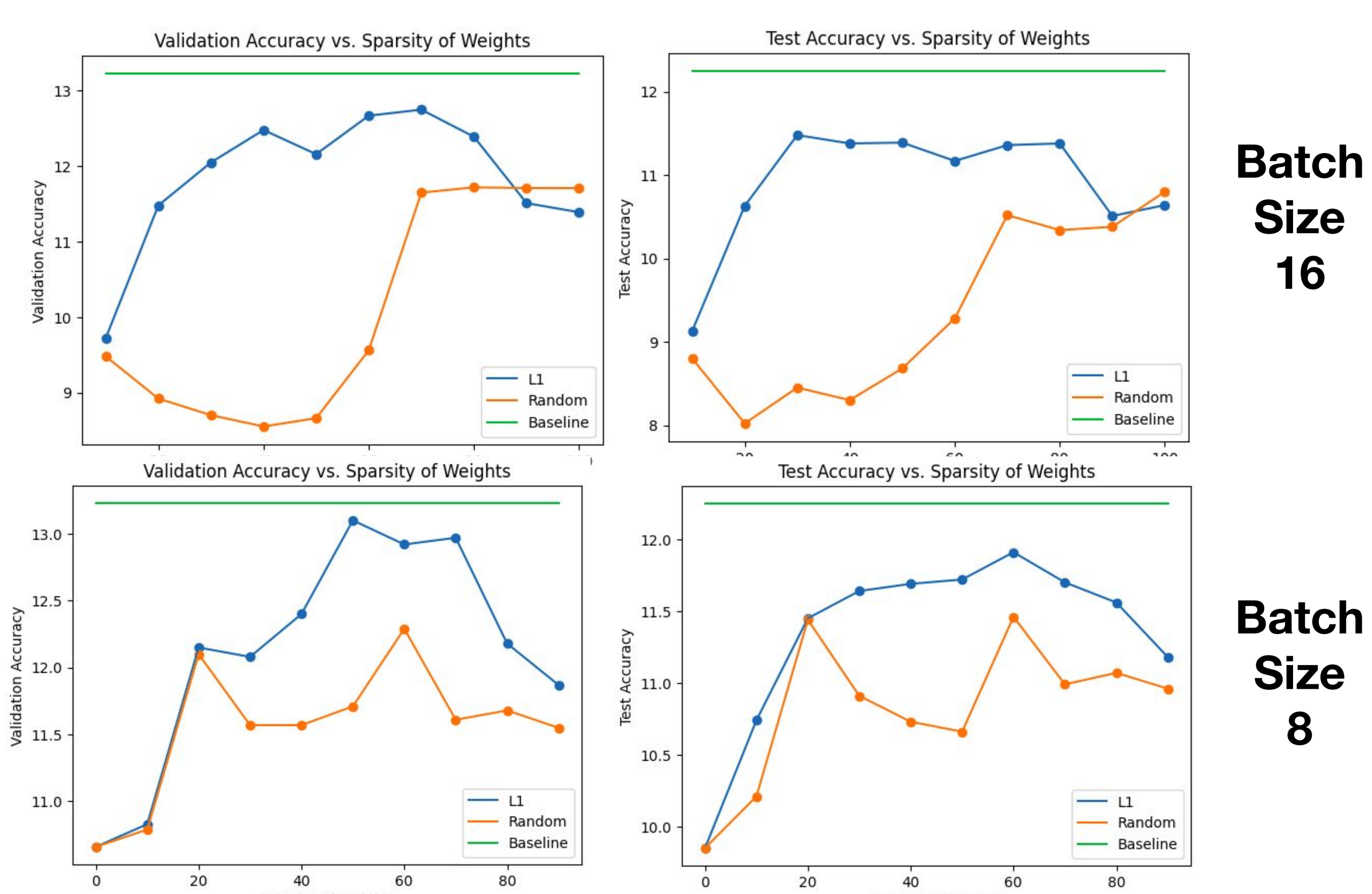
Can pruning be used to understand how language models for text differ from language models for code?

Setting: Ruby code summarization with CodeBERT measured with BLEU score

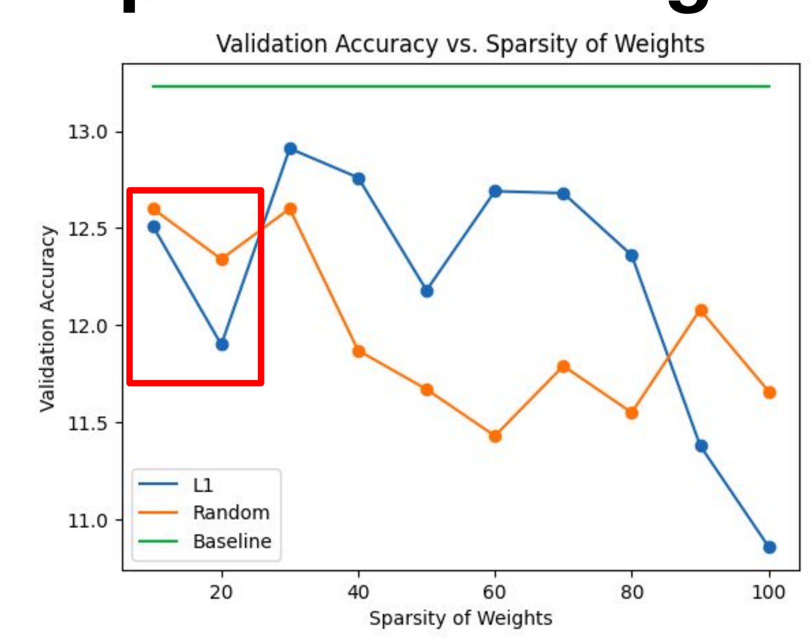
Failed Attempt I: Rewinding to CodeBERT?



Lesson 1: batch size matters a lot
Lesson 2: need to rewind to finetuned CodeBERT?

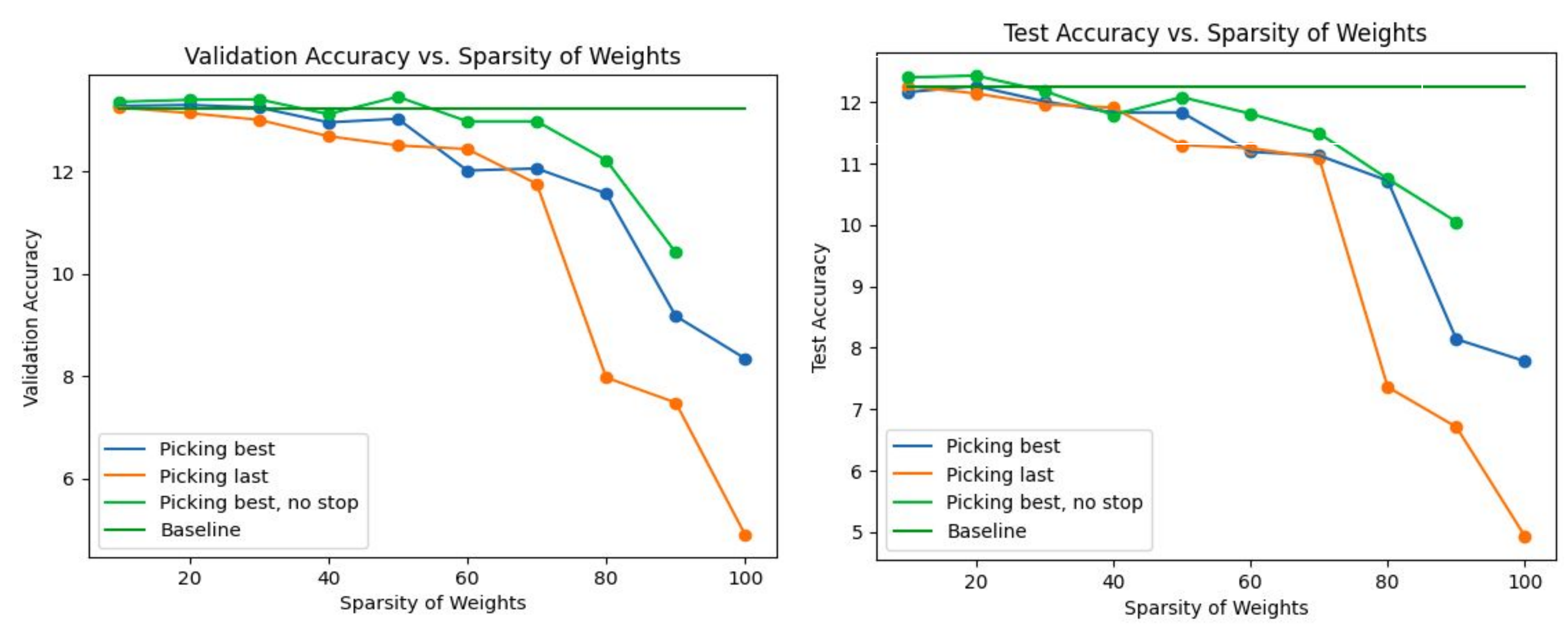
Failed Attempt II: Overfitting?

Random actually performs better?



Hypothesis: are we overfitting every time we finetune?

Final Result

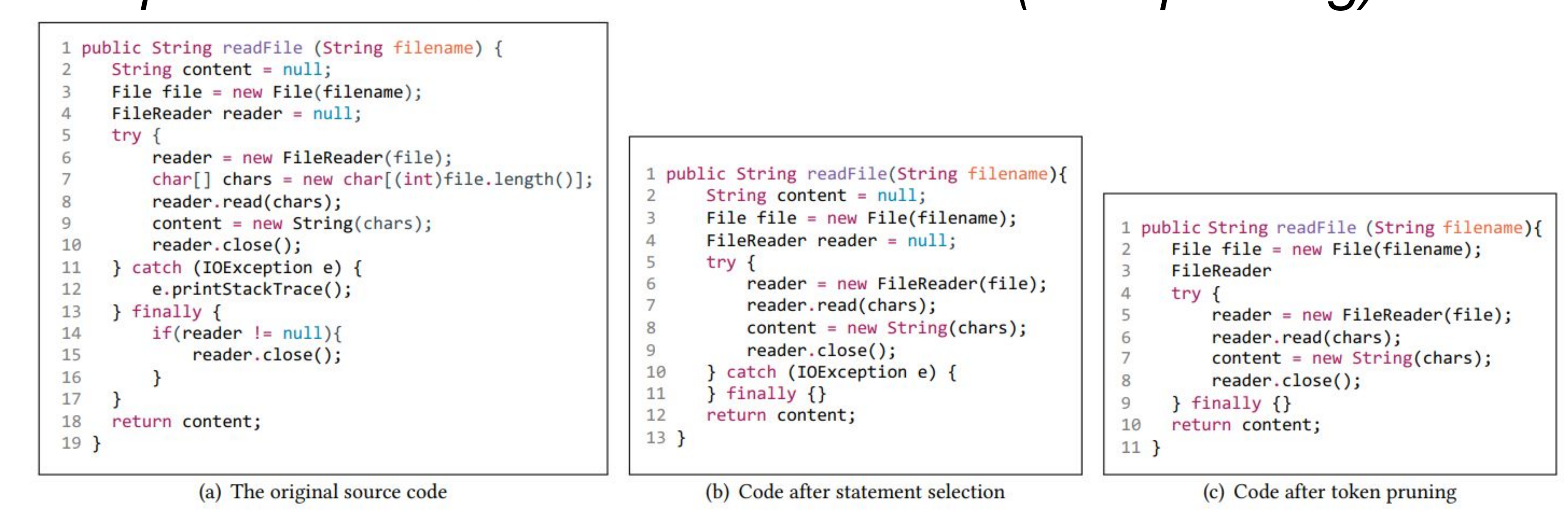


Exciting Directions for Exploration!

Can we look holistically at other code tasks/metrics to understand what is lost when we prune? (CodeT5 on APPS)

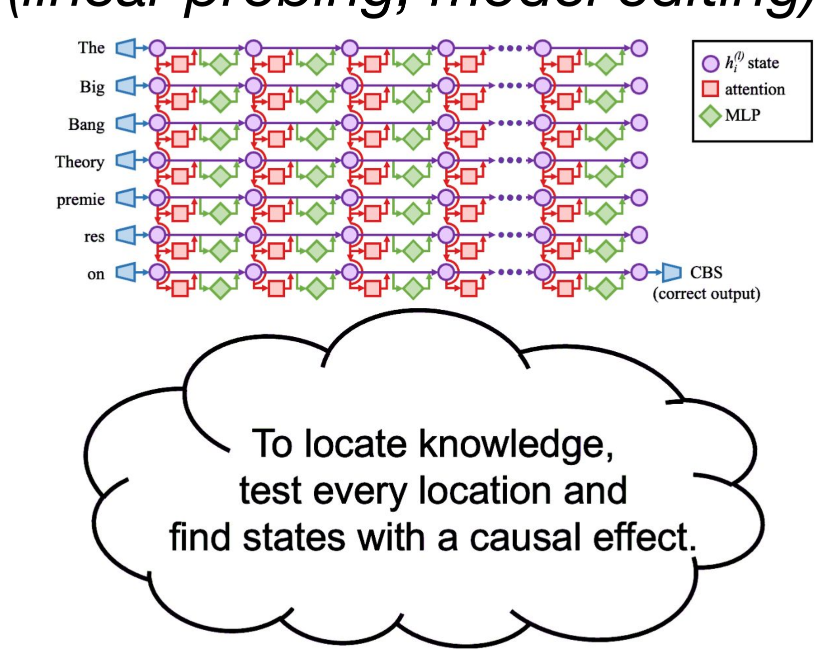
pass@k metric	Dense (%)	OMP(%)	IMP(%)
pass@1	**74.0**	59.0	44.66
pass@2	**93.0**	82.56	69.35
pass@10	**99.99**	99.93	99.71

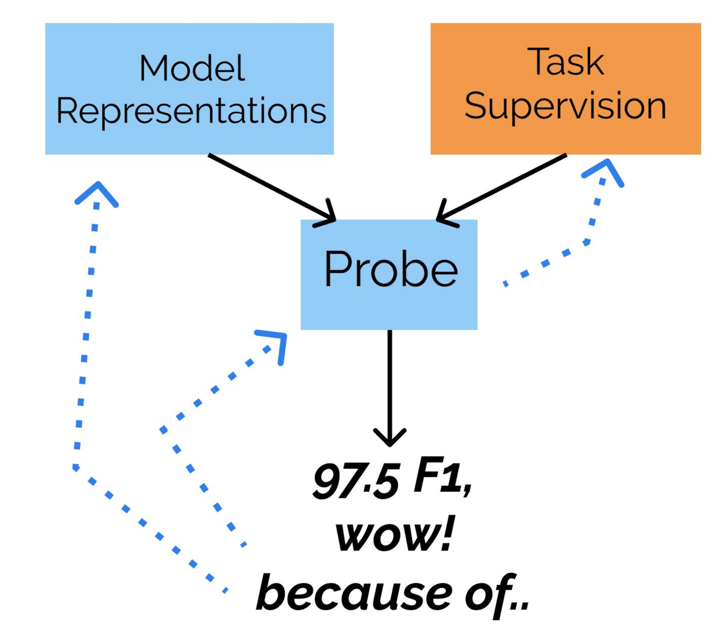
How much information do code models really need to produce and/or summarize code (data pruning)?



Diet Code Is Healthy: Simplifying Programs for Pre-trained Models of Code [Zhang, et al. 2022]

Can we combine pruning and interpretability techniques (linear probing, model editing) to understand what's learned?

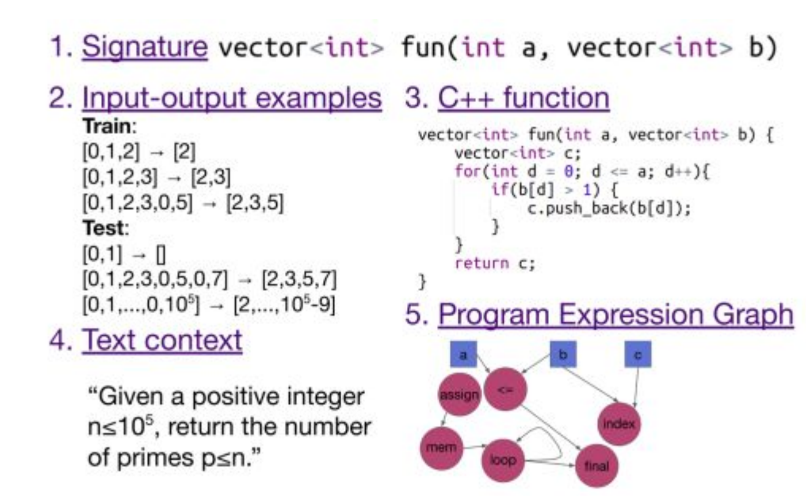




Locating and Editing Factual Associations in GPT [Meng, et al.] *John Hewitt's blog post on Designing and Interpreting Probes*

How can we leverage the structured and precise nature of code to design more efficient language models on them?

- Abstractions
- Precise semantics
- Access to execution information
- Test cases (correctness)
- Compositionality



A large-scale benchmark for few-shot program induction and synthesis [Alet, et al.]