Google Research

Scaling Laws for Multilingual Neural Machine Translation

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Joint Work:

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The unreasonable effectiveness of **Scaling**

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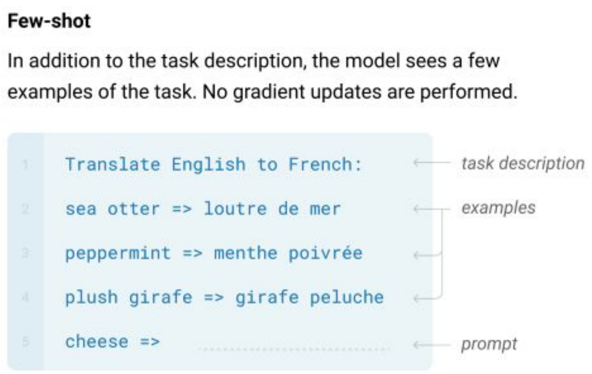
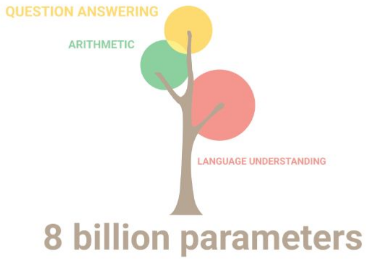
- Current *state-of-the-art* models have (many) billions of parameters





Brown et al. (2020) "Language Models are Few-Shot Learners"
Chowdhery et al. (2022) "PaLM: Scaling Language Modeling with Pathways"

Predicting performance with **Scaling Laws**

- Growing body of literature on predicting the performance of models as we scale
  - In **capacity (*N*)**
  - In **dataset size (*D*)**
  - In **compute (*C*)**

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Model Scaling Exponent

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<u>Irreducible Loss</u>
(Limitations of Transformers)
(Intrinsic Variance in the Task)

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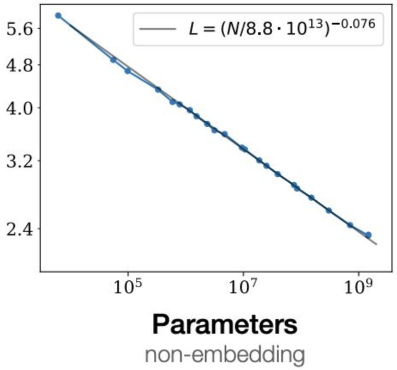
- Follows a **power-law** relationship



Scaling Laws for Machine Translation

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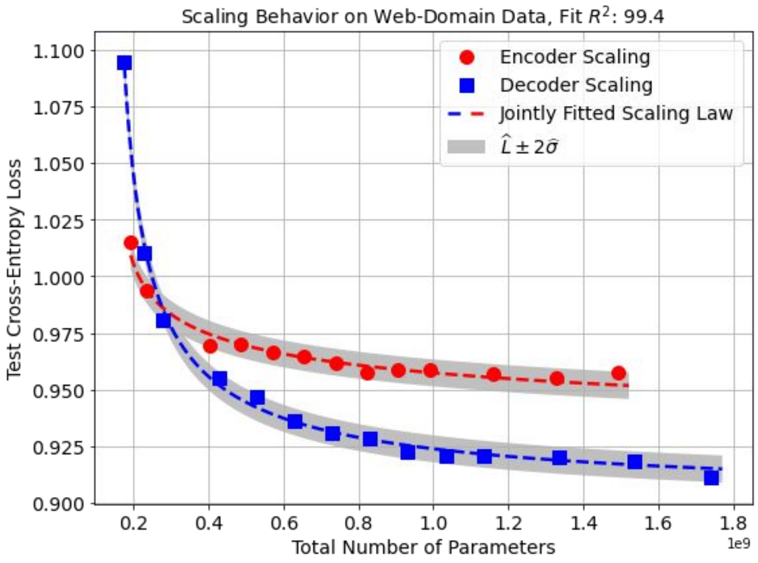

Ghorbani et al (2021). “Scaling Laws for Neural Machine Translation”

Scaling Laws for Machine Translation

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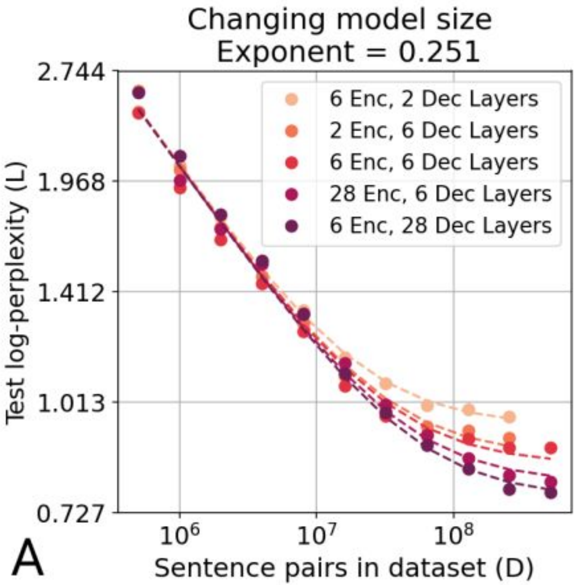
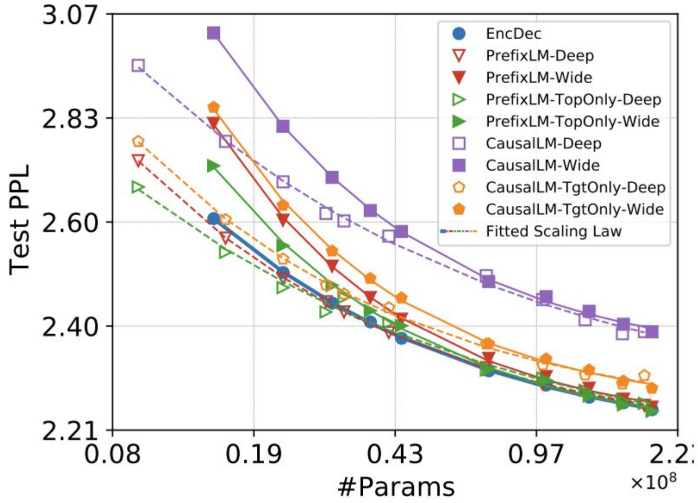
    - Similar laws for data scaling and different architectures





Bansal et al (2022). “Data Scaling Laws in NMT: The Effect of Noise and Architecture”
Zhang et al (2022). “Examining Scaling and Transfer of Language Model Architectures for Machine Translation”

Multilinguality + Scaling = ❤

- Previous works has mostly consider scaling laws **for a single language/task**

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- One important capability that highly benefits from scale is **multilinguality**
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- Massive multilingual models are <u>crucial</u> to break the language barrier in NLP

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*Can we empirically derive scaling laws for multitask/multilingual models the predict their performance for **any** weighting of the languages in the training set?*

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- Suppose we want to train a model with parameters $\boldsymbol{\theta} \in \mathbb{R}^p$ for K tasks
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- Typically implemented *implicitly*
    - Sample observations from each task according to its weight on the loss

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Data-Rich Multi-Task Optimization

- In the presence of sufficient data for each, there is a *performance trade-off frontier*

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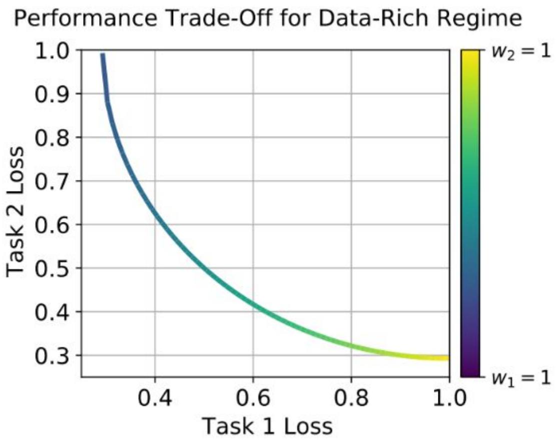

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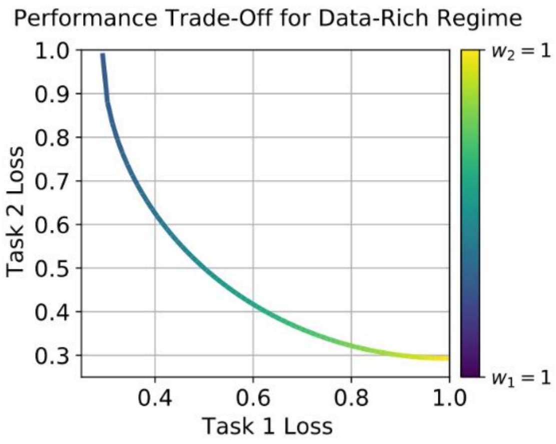

*Can we empirically derive scaling laws for multilingual models in the **data-rich** scenario?*

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Setting: Interference

- We attempt to first fully understand **data-rich** scenario

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- We attempt to first fully understand **data-rich** scenario
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    - English→German+Chinese, English→German+French and German+Chinese→English
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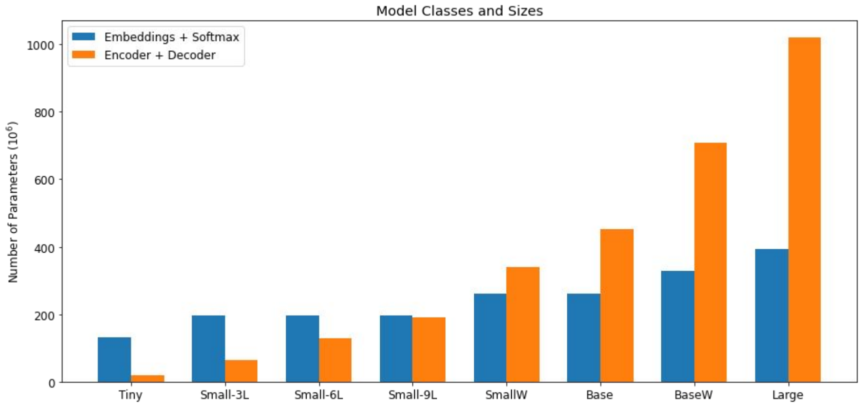

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- We vary the task **weight/probability** for each language (different mixture probabilities)

$$p_1 \in [0,\ 0.01,\ 0.05,\ 0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9,\ 0.95,\ 0.99,\ 1] \qquad p_2 = 1 - p_1$$

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- We evaluate on **in-domain** and **out-of-domain** test sets

Results: English⟶German+Chinese

- We then fit individual scaling laws for each task weighting **for both languages**

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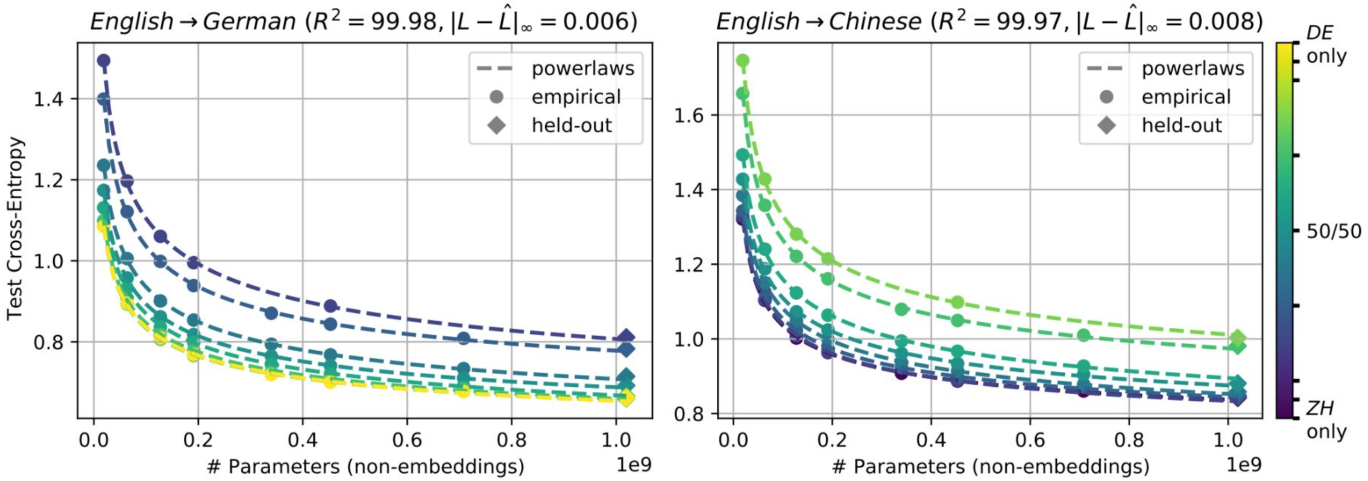

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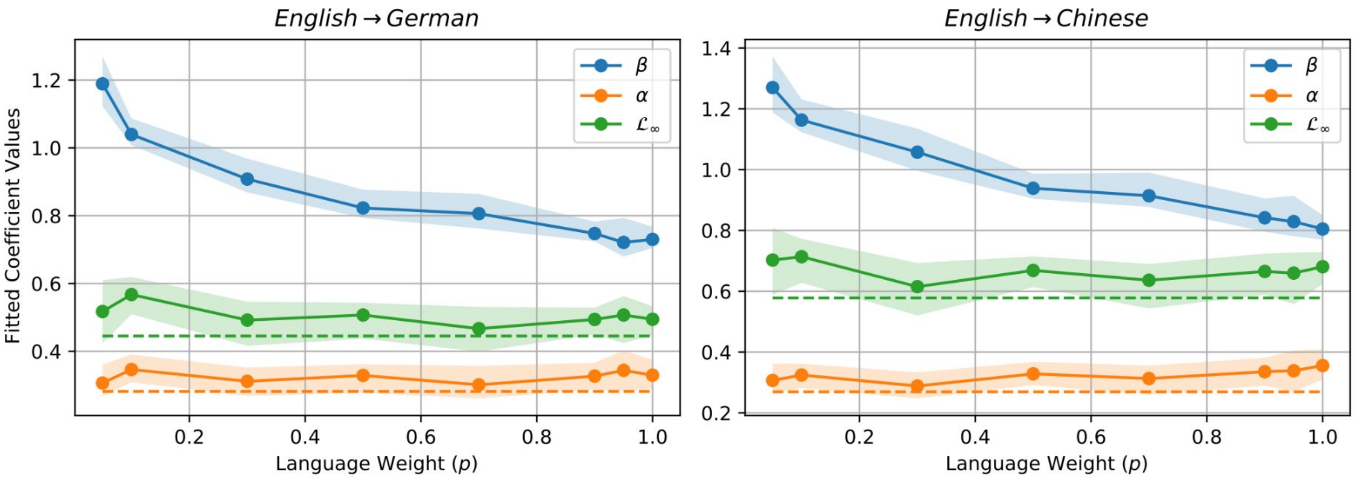

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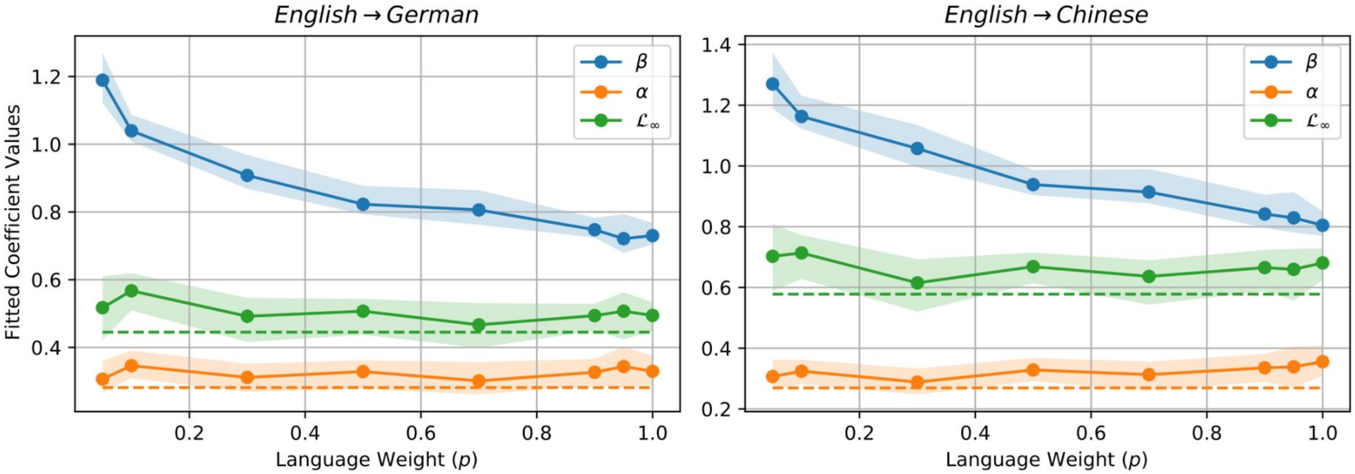
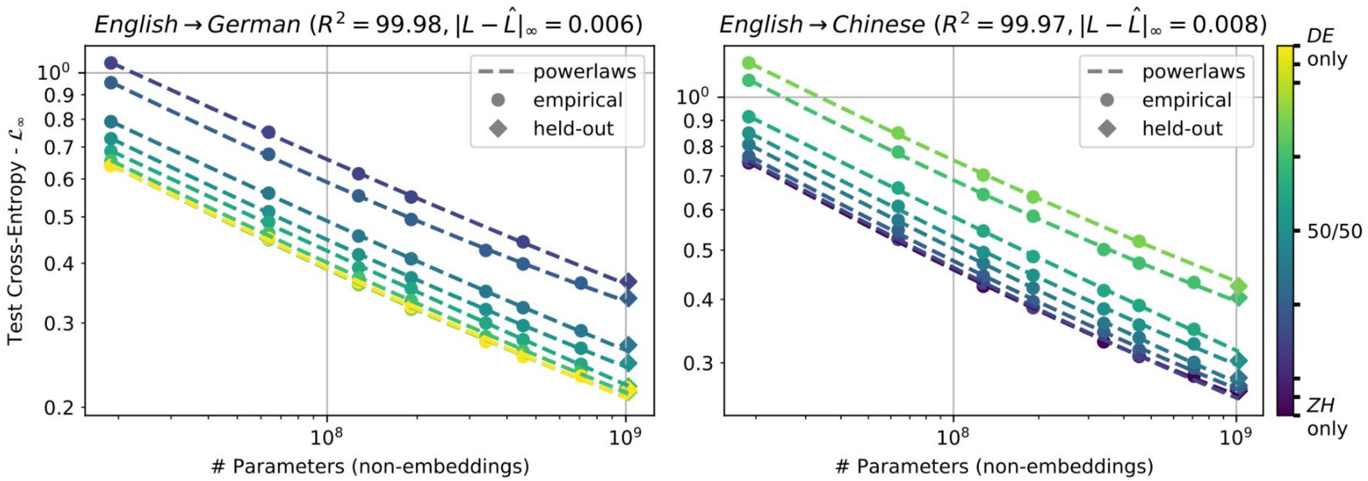


- Scaling exponent and irreducible loss seem to be (~) constant across mixture probabilities!

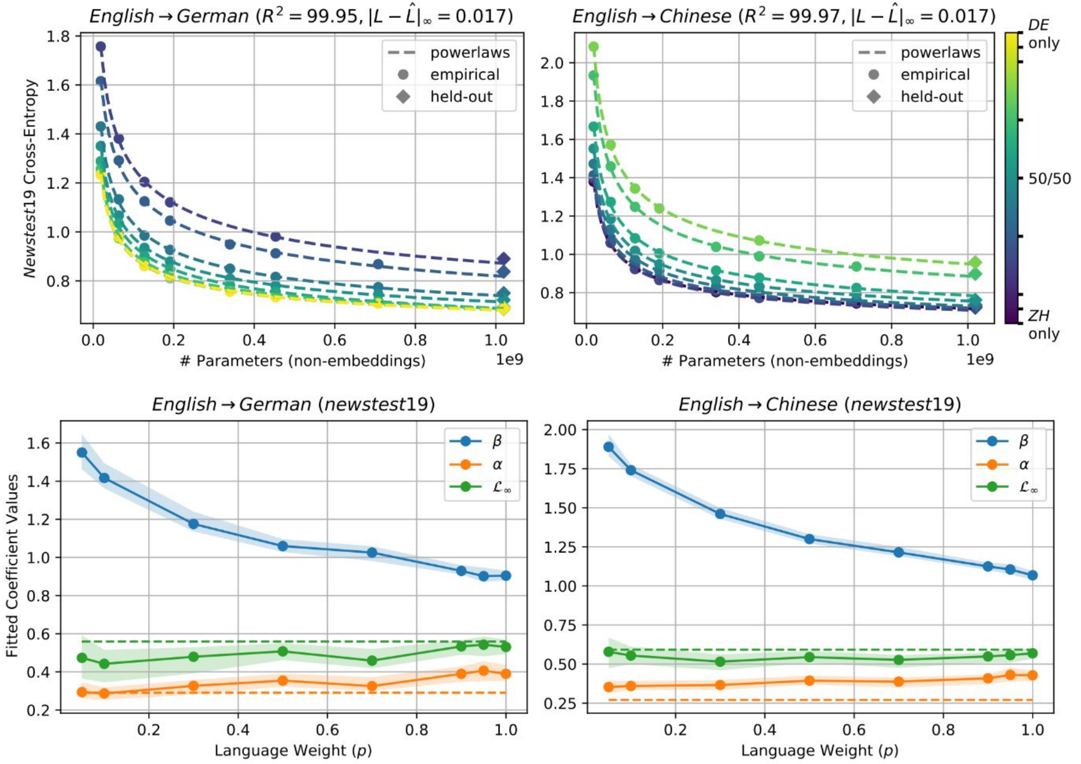
Results: English⟶German+Chinese

- When we subtract a constant for irreducible loss, we plot in log-log axes



Results: Out-of-Domain

- These findings hold for different domains



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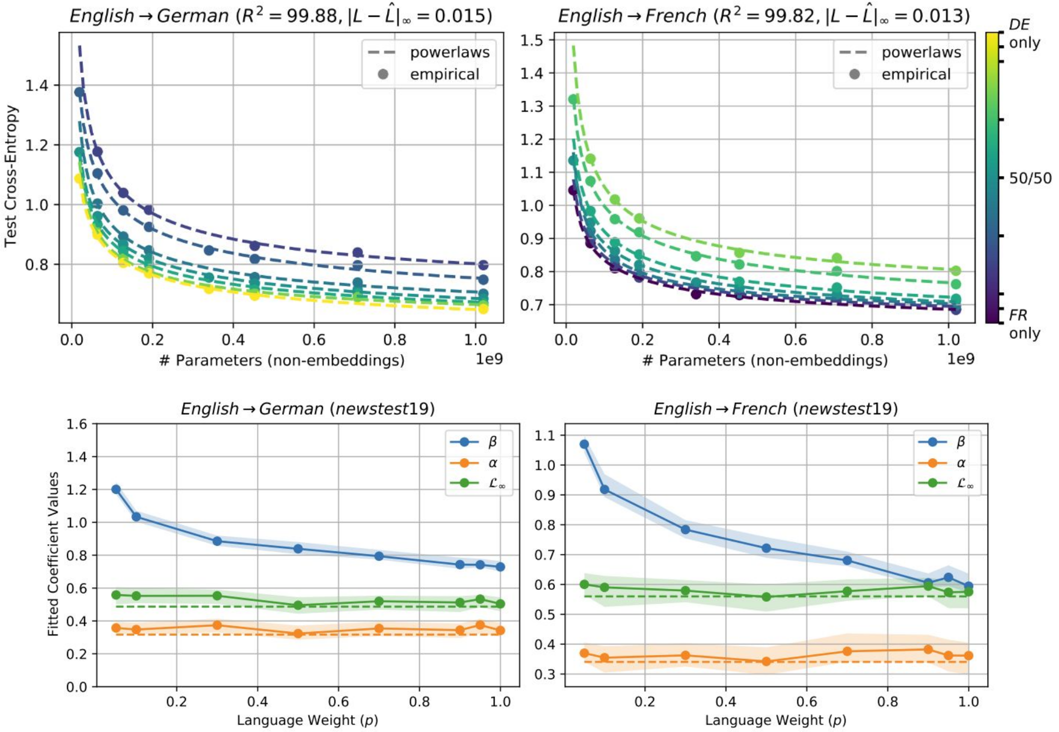
Results: Other Language-Pair Combinations

- These findings hold for different language-pair combinations



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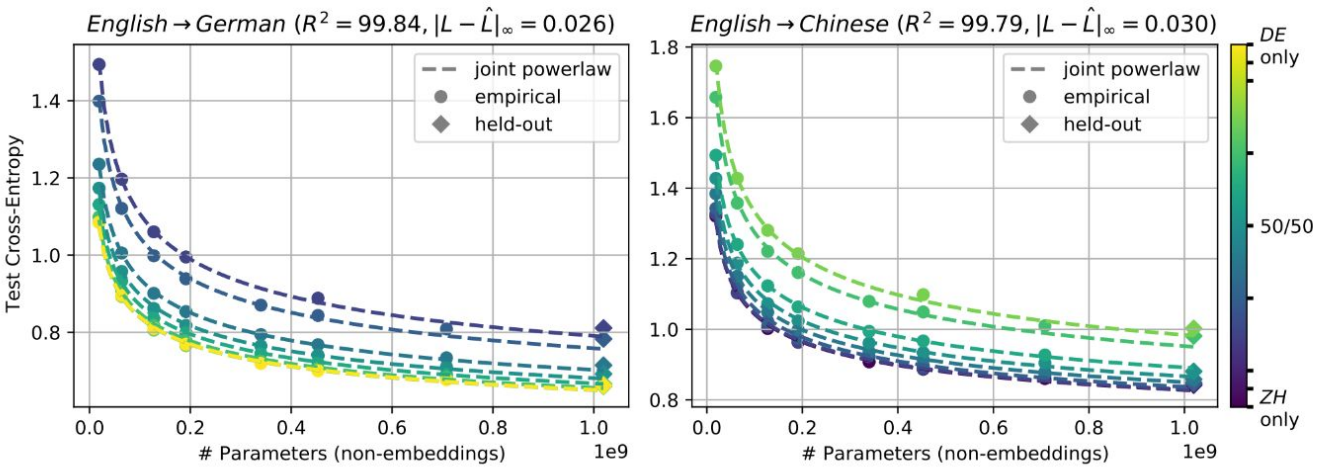
  - Same exponent and irreducible loss for all task weights, different multipliers for each
  - ~1 coefficient per mixture weighting!

Jointly Modeling Multitask Scaling: En⟶De+Zh

- A joint scaling law provides a good fit for most task weightings!



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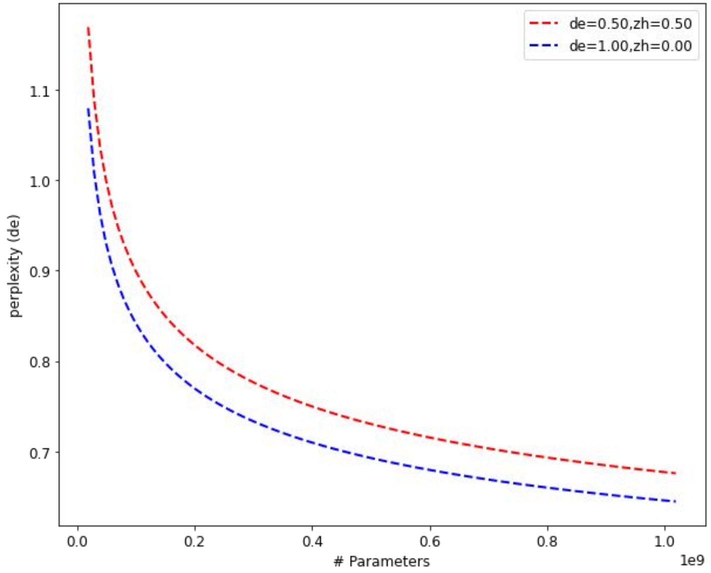

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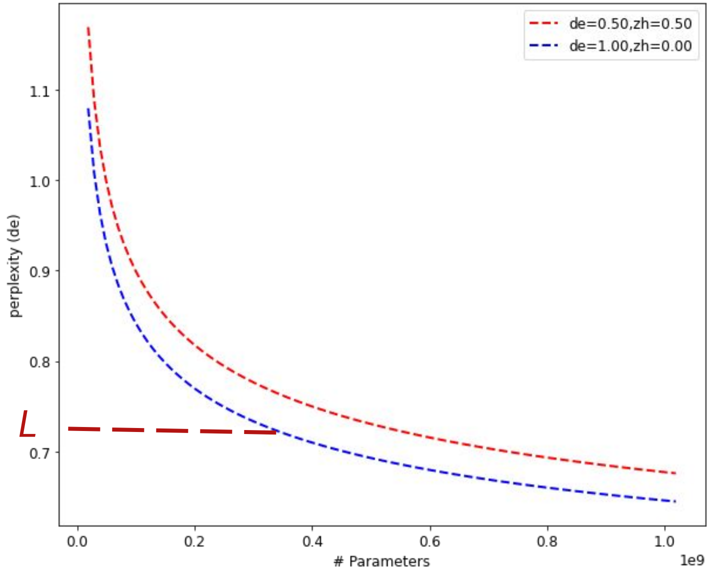

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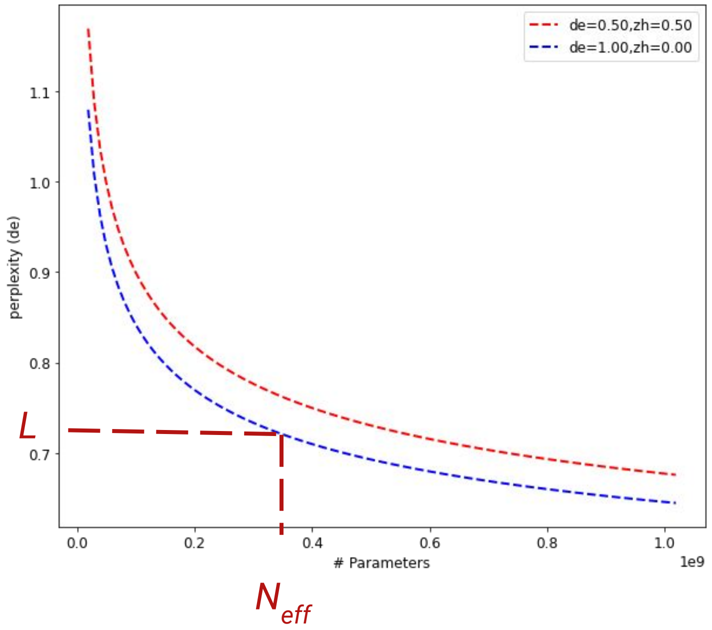

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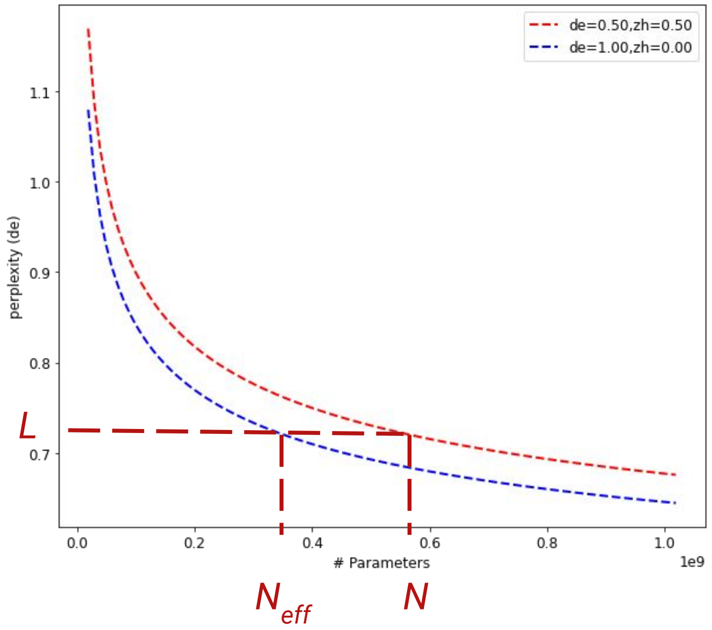

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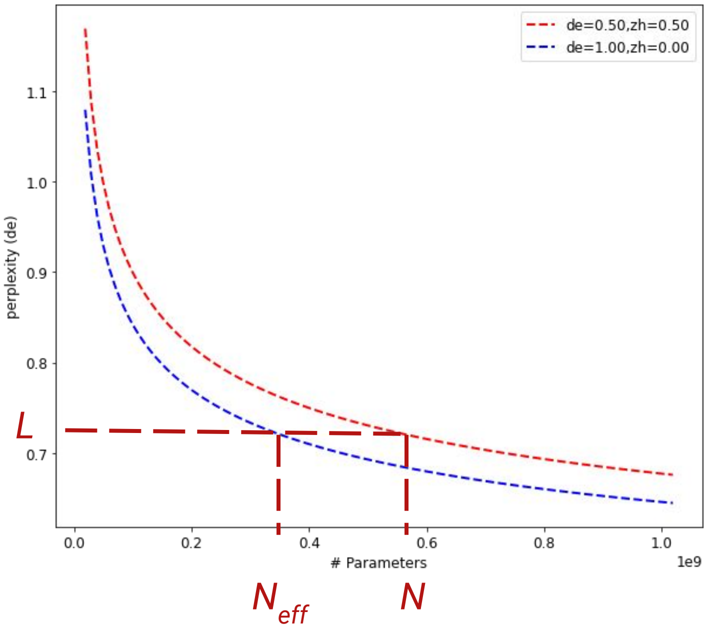
- We can empirically compute this

  effective parameters number

$$N_{eff}^{(i,p)} = \left(\frac{\beta_{1,i}}{\beta_{p,i}}\right)^{\frac{1}{\alpha_i}} N$$



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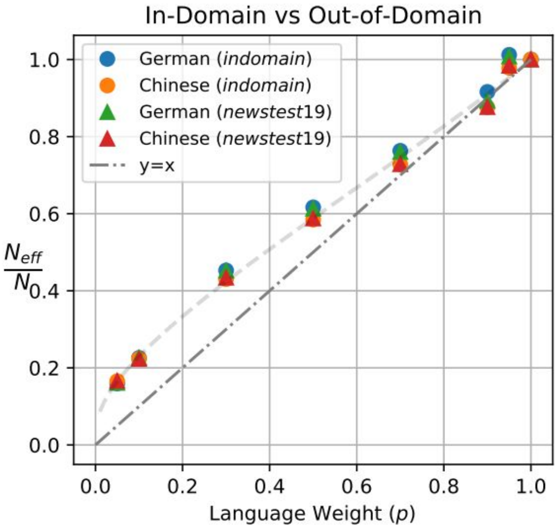

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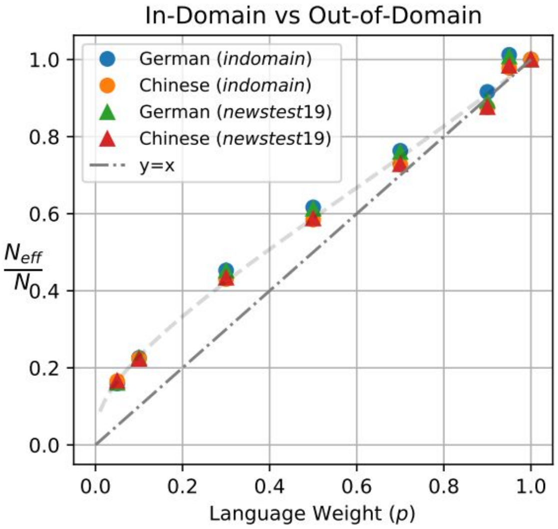

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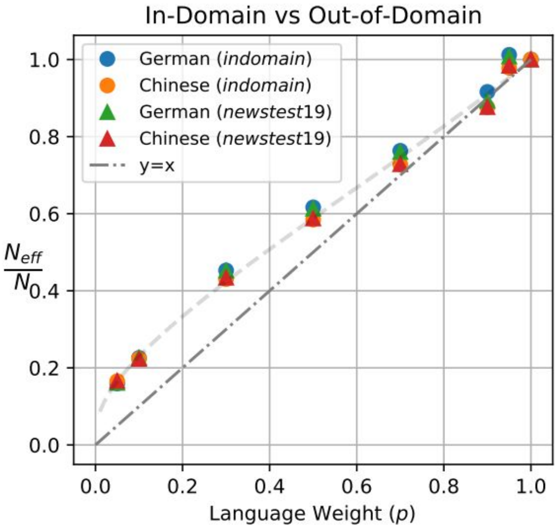

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- Capacity splitting is similar for in-domain and out-of-domain

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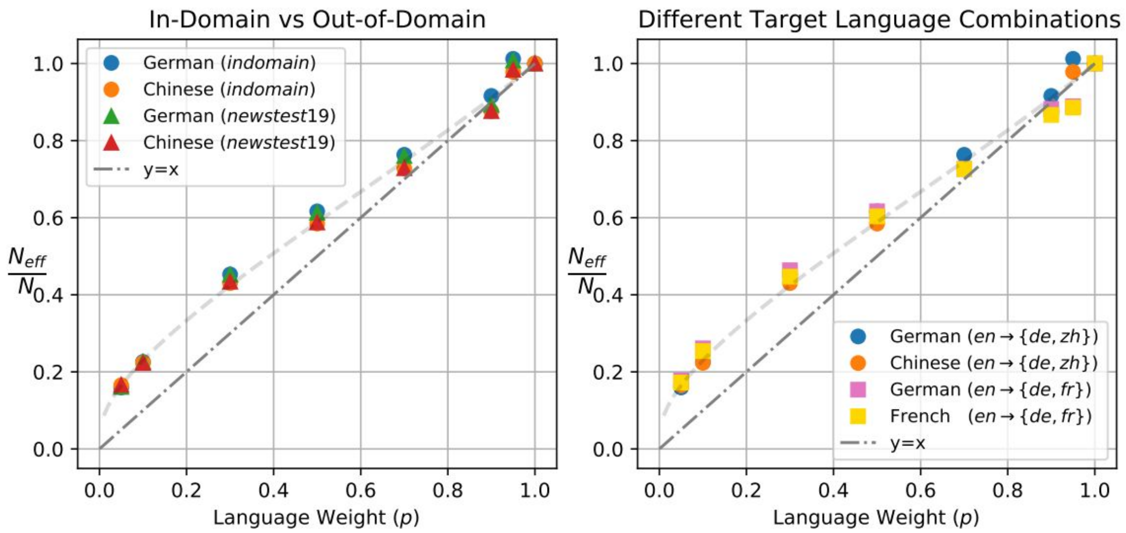

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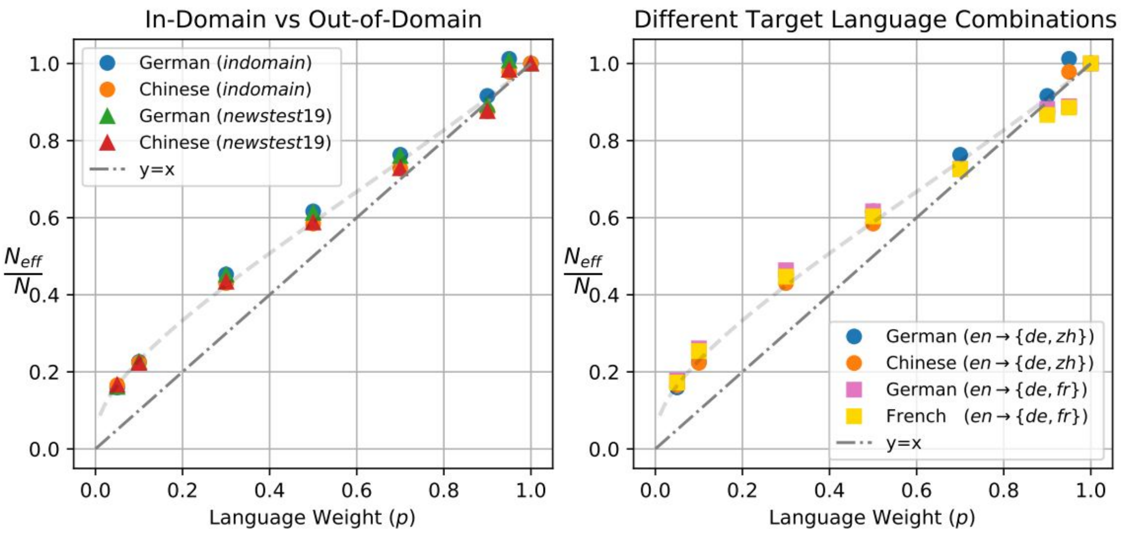

- Despite being more similar, capacity for English→German+French are very similar
  - Very little “sharing” of parameters between languages

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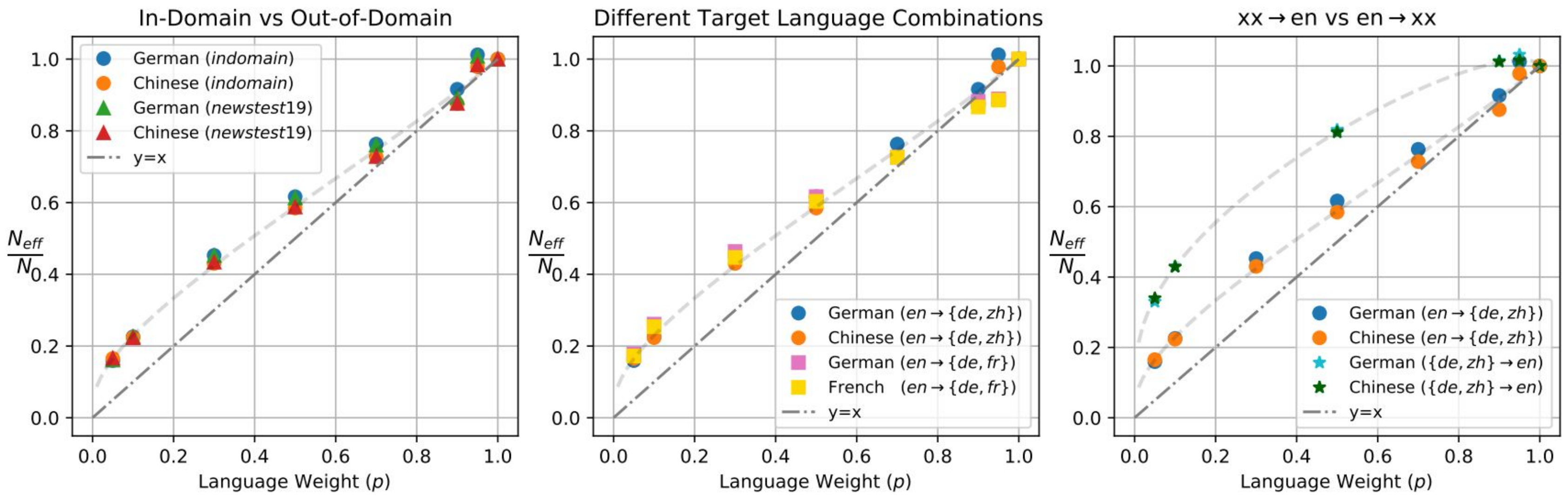

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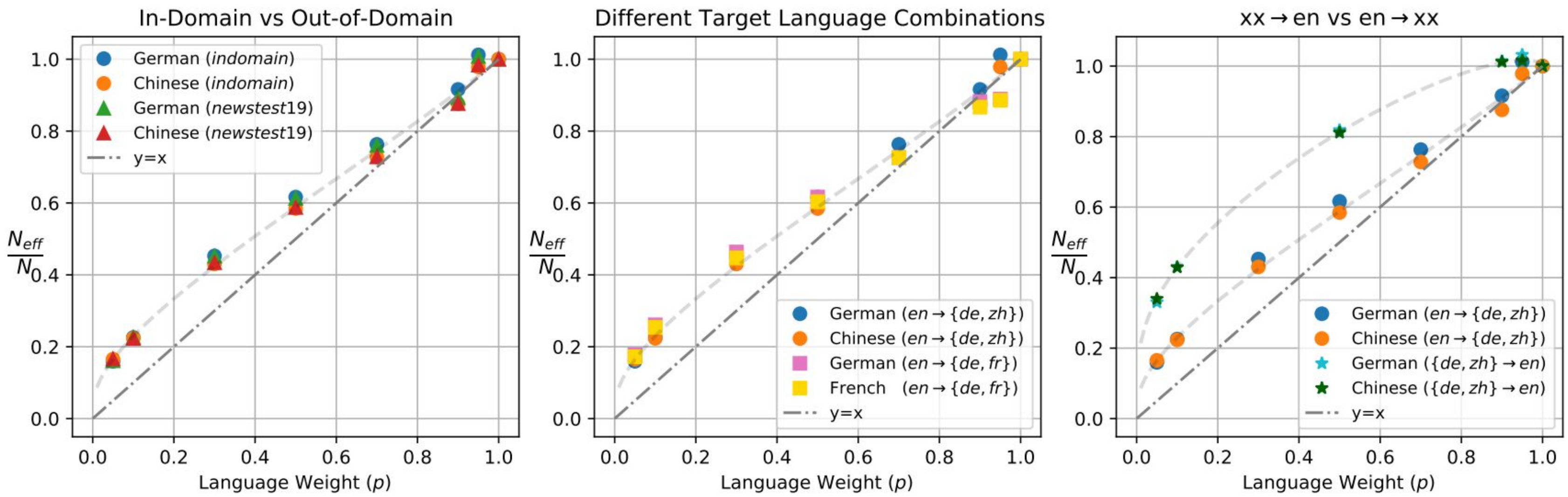

- In contrast, *"direction"* plays an important role in effective capacity
  - Positive synergy between tasks and higher "parameter sharing"

Guiding Task Balancing

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- To extend to unseen task weightings, we instead focus on estimating $f(p)$

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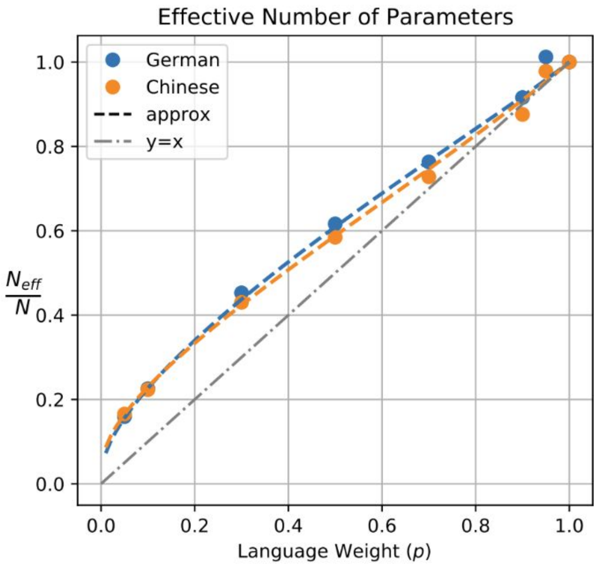
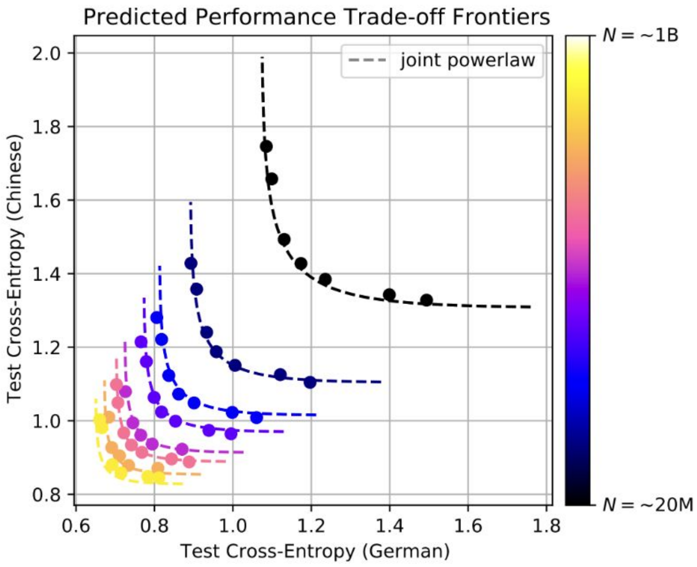
- With this parameterization, we can predict performance **for any task weighting**

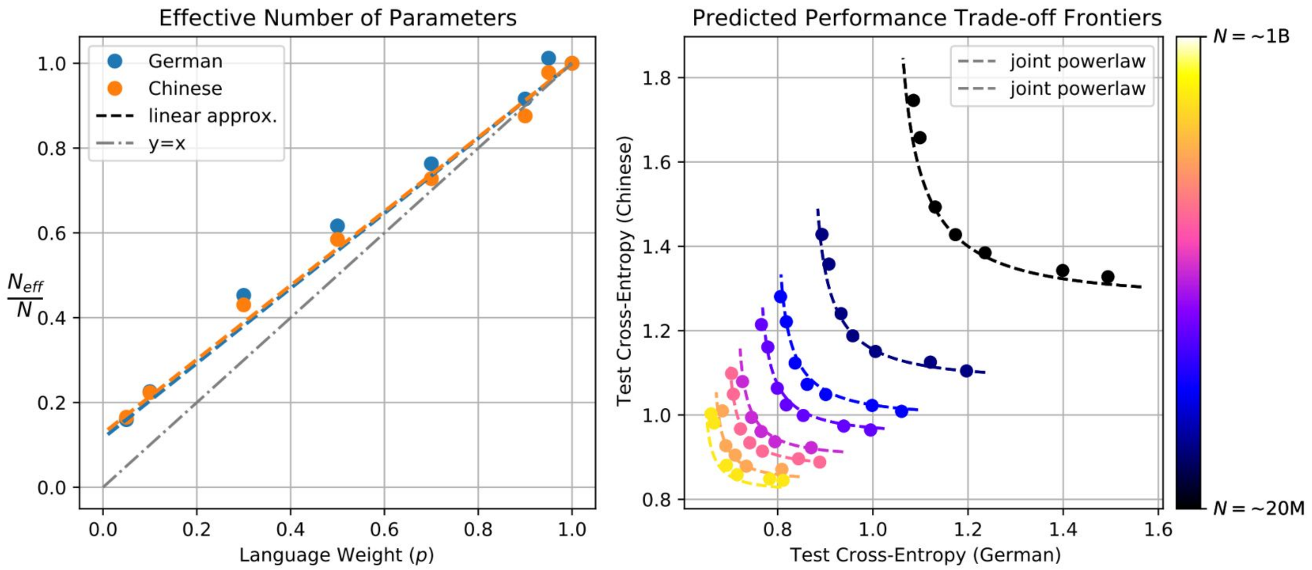
Guiding Task Balancing: En⟶De+Zh





- Almost perfectly captures the full task performance frontier across a variety of model scales.

Guiding Task Balancing: Simpler Models



- A simpler linear model is still able to perform relatively well
  - Requires training less models/task weightings

$$\hat{f}_i(p) = c_1(p-1) + 1.$$

Translation Quality

- In MT research, quality is often measured via *automatic metrics* opposed to cross-entropy
  - BLEU, ChrF, BLEURT, COMET, …
  - These metrics take into account the *decoding* problem
  - Likelihood might not correlate human preference in certain situations

Translation Quality

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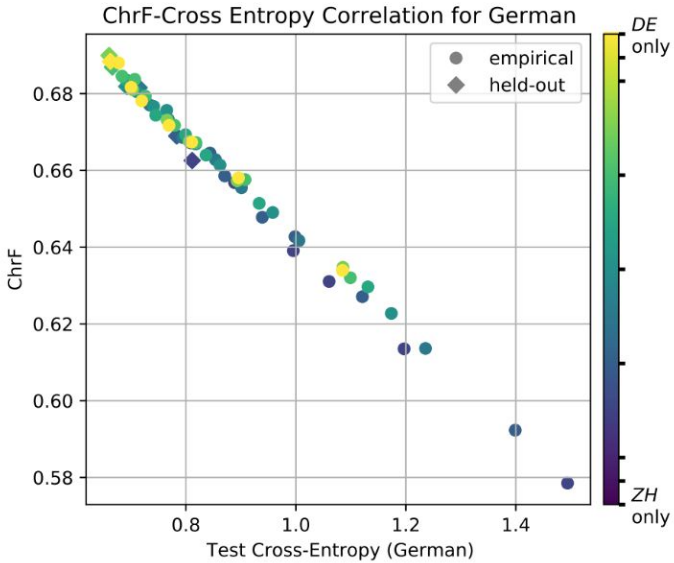
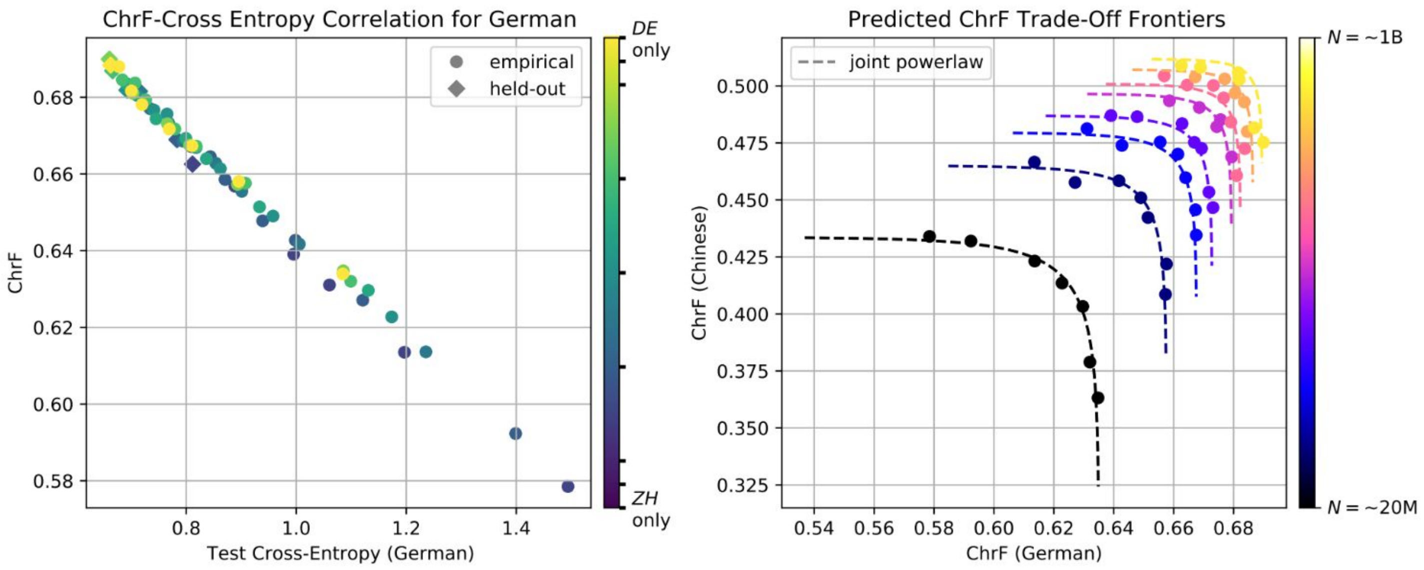
  - BLEU, ChrF, BLEURT, COMET, …
  - These metrics take into account the *decoding* problem
  - Likelihood might not correlate human preference in certain situations
- To ensure the practical applicability of results, we repeat our analysis for ChrF and BLEURT
  - Obtain translations from model by decoding with *beam search*

Translation Quality: ChrF



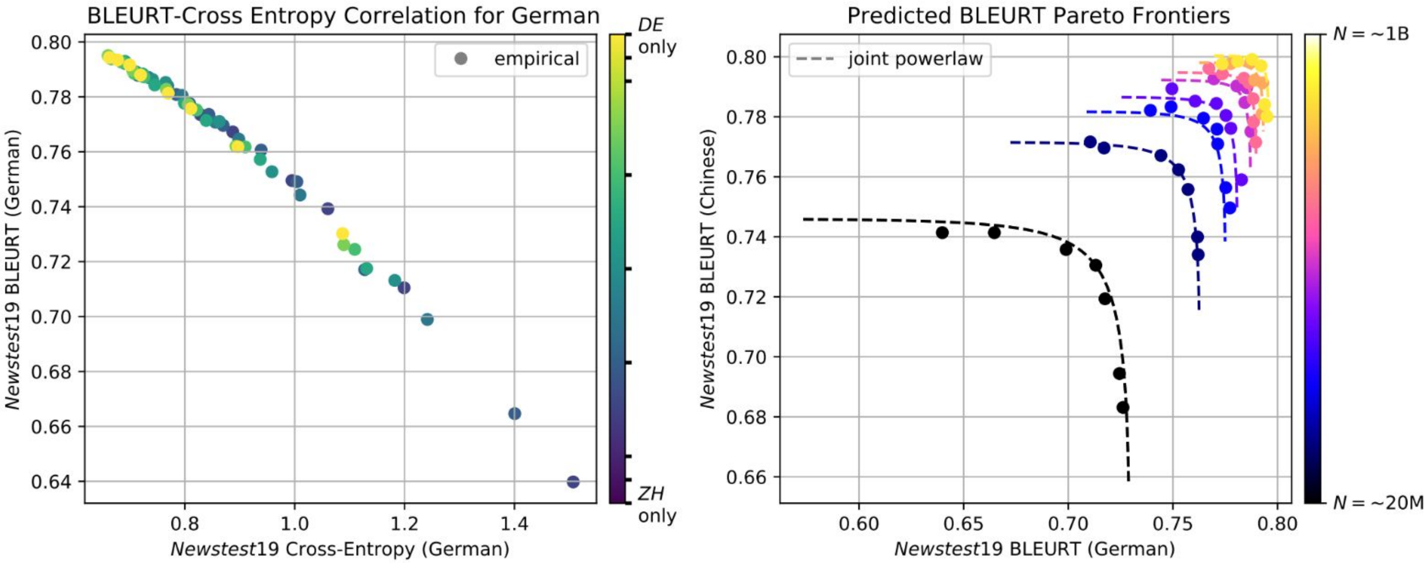
- ChrF has an almost linear relationship with perplexity

Translation Quality: ChrF



- ChrF has an almost linear relationship with perplexity
- We are able to capture the trade-off frontier well

Translation Quality: BLEURT



- Similar findings for BLEURT in *out-of-domain* test sets

Google

Conclusion & Future Work

- The scaling behaviour of multilingual models in an <u>interference</u> scenario is surprisingly simple
  - Almost constant scaling independent of task weight
  - Language/task similarity plays a limited role
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Conclusion & Future Work

- The scaling behaviour of multilingual models in an interference scenario is surprisingly simple
  - Almost constant scaling independent of task weight
  - Language/task similarity plays a limited role
  - “Direction” matters for parameter sharing

- As future work, we plan investigate:
  - Multi-task optimization for more diverse tasks (LMs + Code Modelling for example)
  - The scaling properties in the transfer scenario

Generalizing to More Tasks

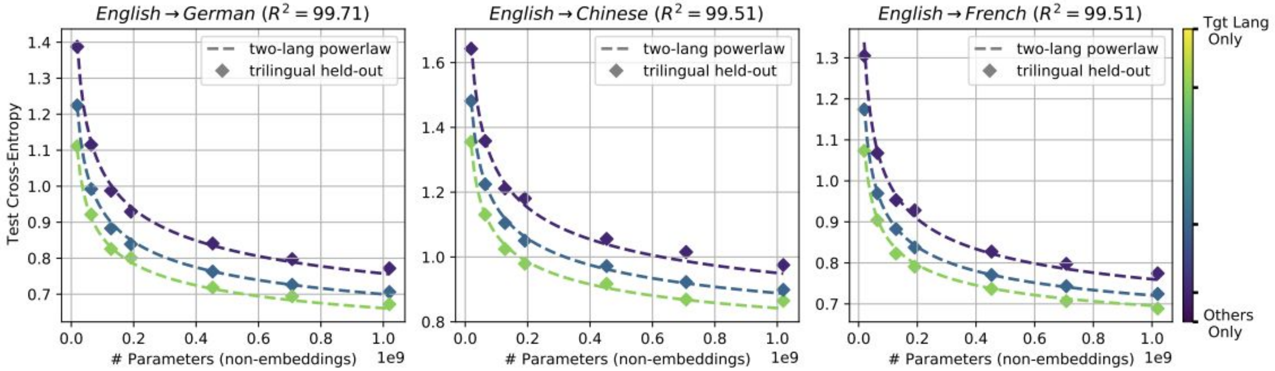

Figure 20. The evolution of the (in-domain) test cross-entropy loss with model size for En→{De, Fr, Zh} models, as well as the fitted scaling laws fitted for En→{De, Zh} (left and middle) and En→{De, Fr} (right). The color represents the weighting of the languages. Note that we don't show the *zero-shot* behavior.

Extension to Low-Resource Languages

On the Pareto Front of Multilingual Neural Machine Translation

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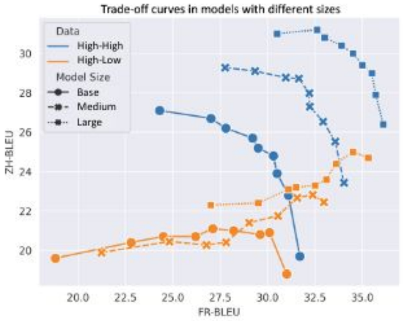

Figure 4: Generalization Performance (BLEU) trade-off curves for English→{French, Chinese} under different model sizes and data distributions. The collapse of Pareto front exists in different model sizes when the training data is imbalanced.