Natural Language Processing for Low-Resource and Marginalized Language Varieties

Pillar II: Learning

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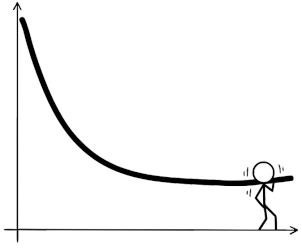
Recap

Pillar I: Data

- Low-resource languages suffer from the **long tail** of data availability



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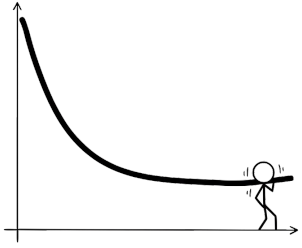

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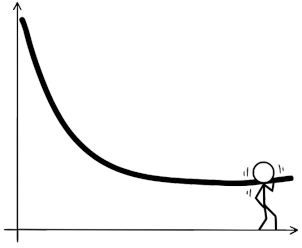

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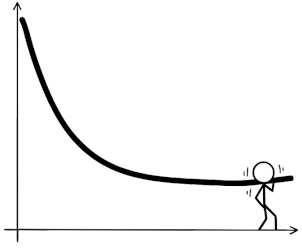

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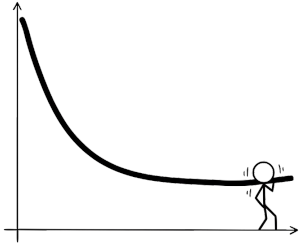
  - **Augmentation**: back-translation, bitext mining, BLI, gamification



Pillar II: Learning

Learn a model to map an input X into an output Y:

Input X	Output Y	Task
Text	Text in another language	Machine Translation
Text	Response	Dialog
Speech	Transcript	Speech Recognition
Text	Linguistic Structure	Language Analysis

But how?

From X to Y

Paradigm Shifts in NLP

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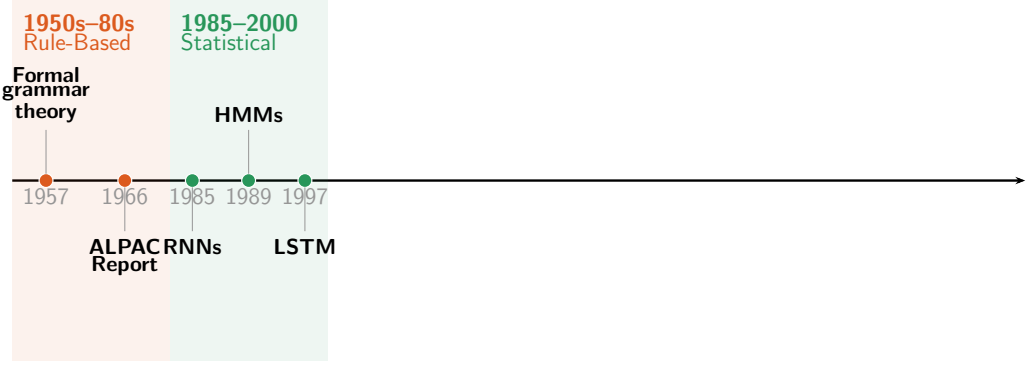

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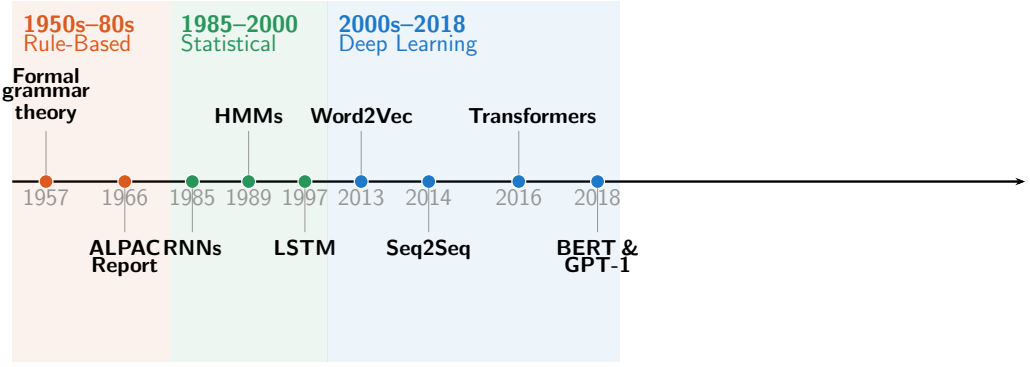

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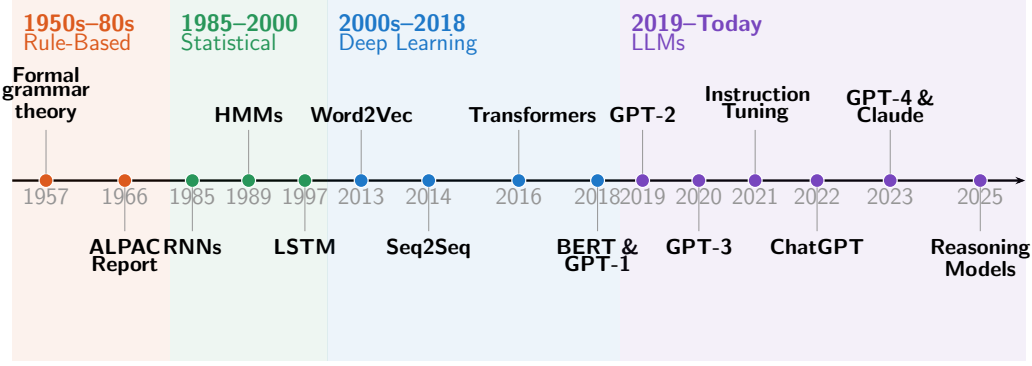

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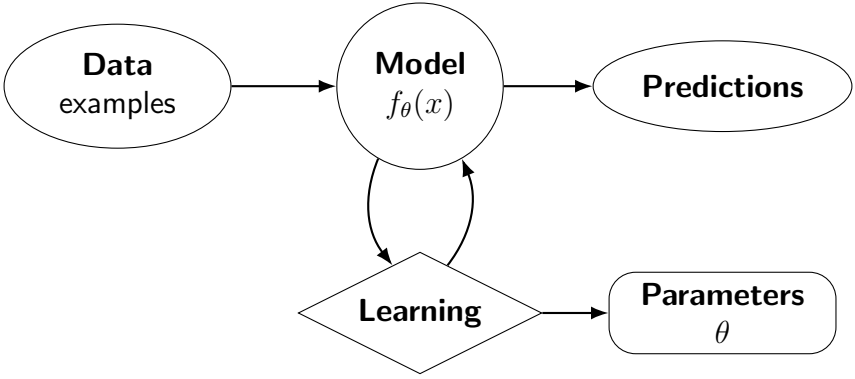
Example (Forms of feminine nouns in German in Hunspell)

```
SFX F N 7
SFX F   0     nen          in
SFX F   e     in           e
SFX F   e     innen        e
SFX F   0     in           [^i]n
SFX F   0     innen        [^i]n
SFX F   0     in           [^en]
SFX F   0     innen        [^en]
```

Beyond rules: learn from the data

Learn a model to map an input X into an output Y: Adjust a model's parameters using data to capture patterns and improve prediction accuracy.



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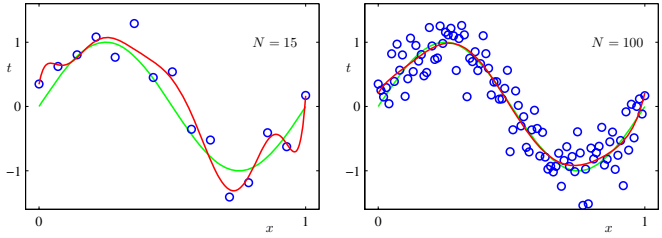

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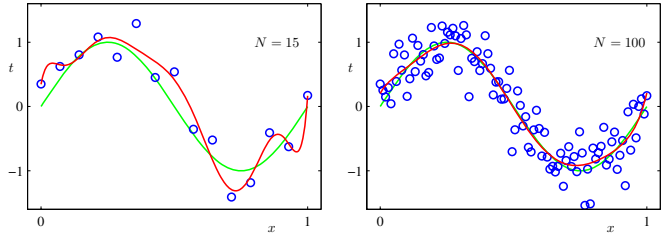

Efficiency of learning methods depends on:

- **Data**: quality, size, type
- **Task**: complexity, structure of the output space
- **Model**: capacity, inductive biases, number of parameters

Learning Paradigms

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- **Reinforcement Learning**: An agent learns by interacting with an environment and receiving rewards
  e.g., dialog systems

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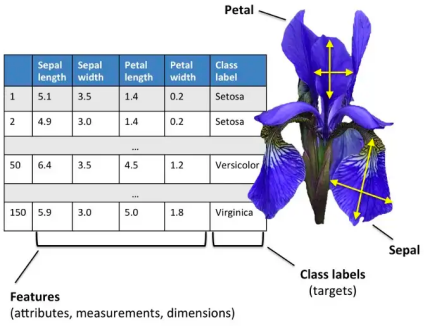

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1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
			...		
50	6.4	3.5	4.5	1.2	Versicolor
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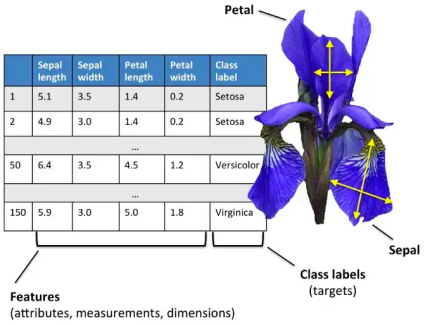

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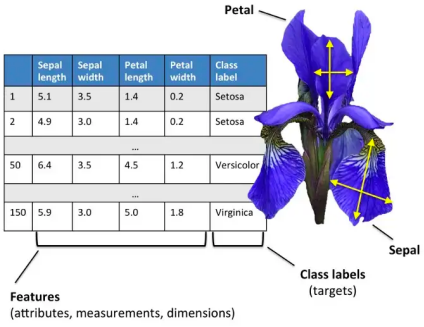
- Feature engineering is labor-intensive and does not scale across languages or domains



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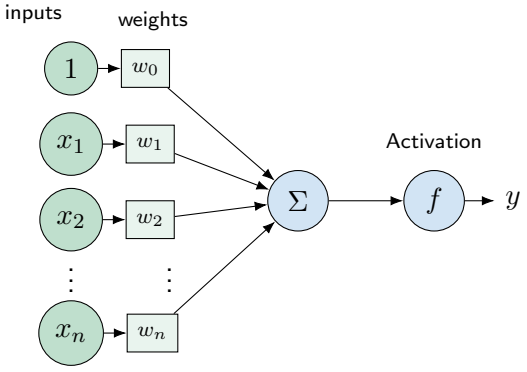
Neural Networks: The Basics

- A **perceptron**: weighted sum of inputs passed through an activation function



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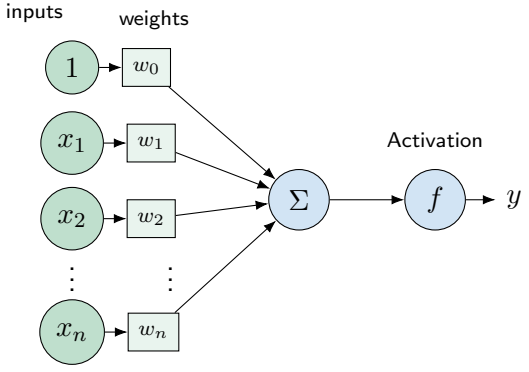

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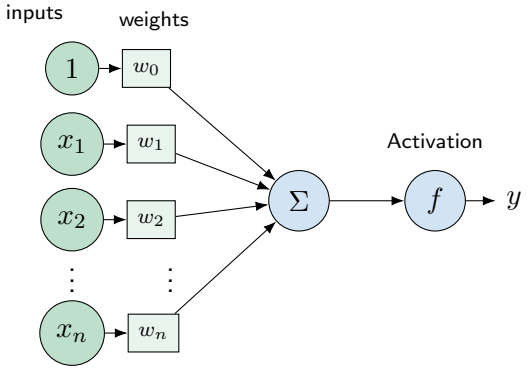

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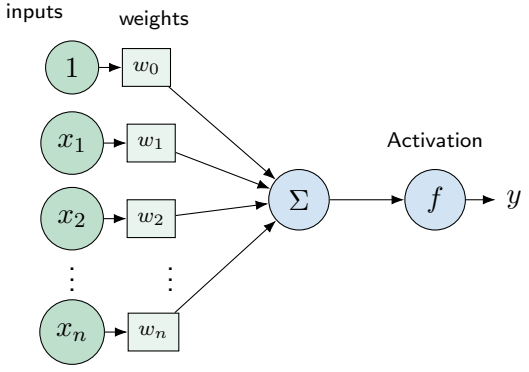
- Non-linear activation functions allow learning complex boundaries



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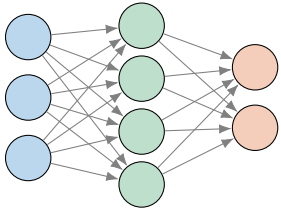

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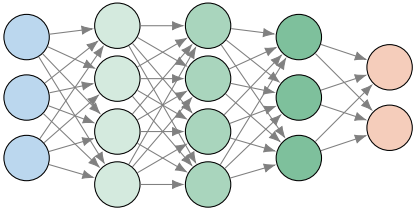

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- Breakthrough applications: image recognition, machine tranlsation, speech recognition

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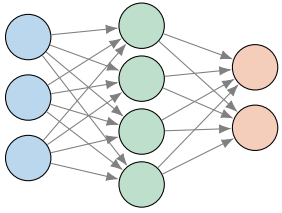

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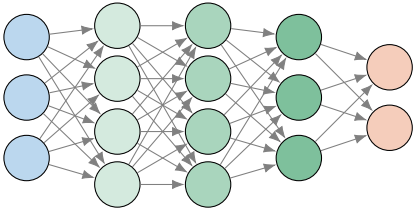

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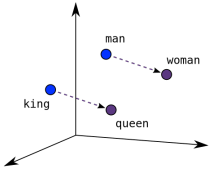
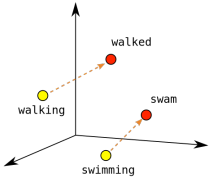
- Represent words as dense vectors in a continuous space



Male-Female



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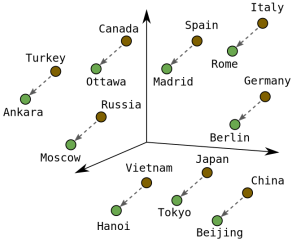

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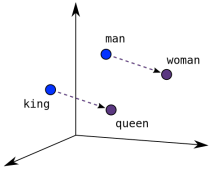

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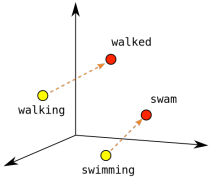

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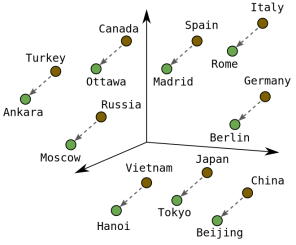

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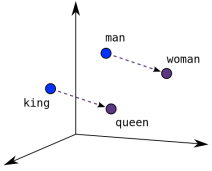

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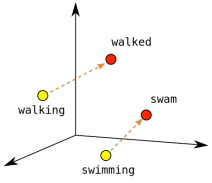

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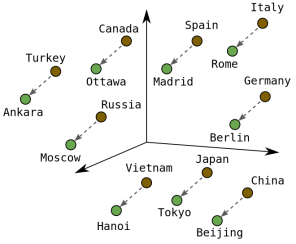

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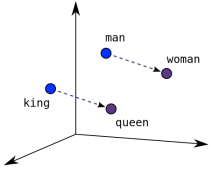
- Foundation for all subsequent neural NLP work



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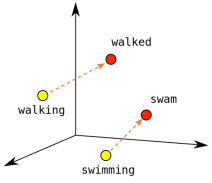

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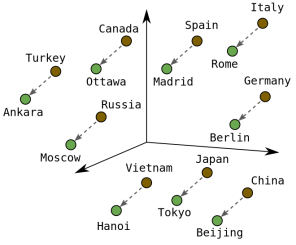

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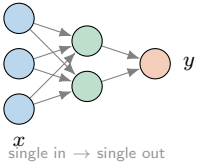

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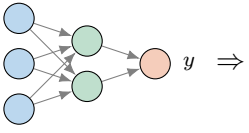

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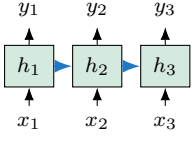

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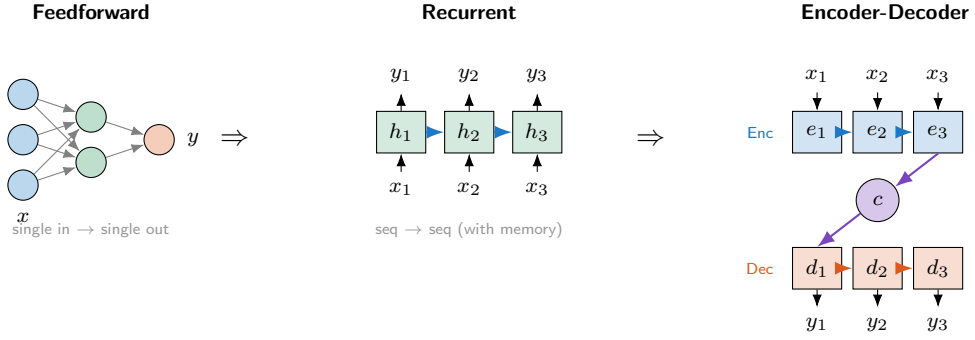

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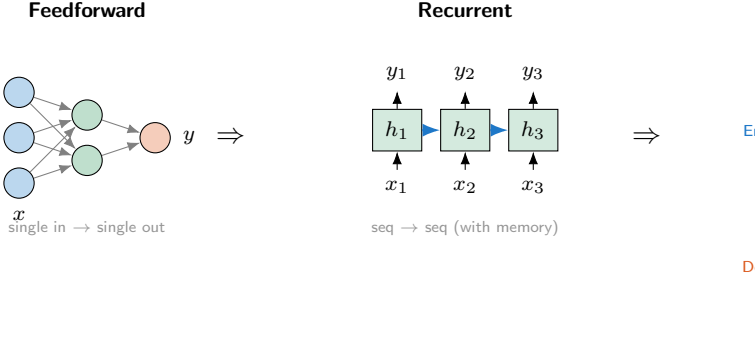

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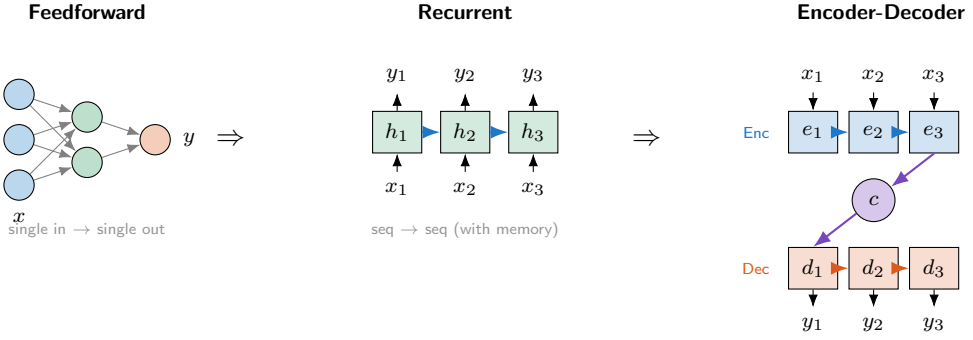
- Vanilla RNNs struggle with long-range dependencies ($\rightarrow$ LSTM)



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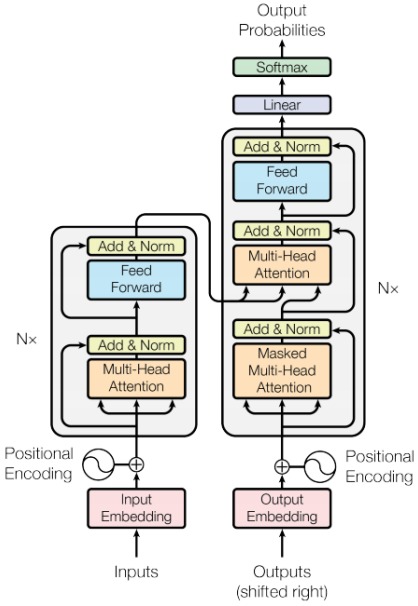

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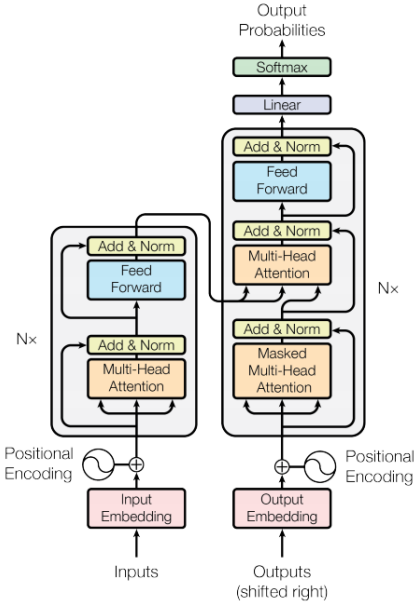

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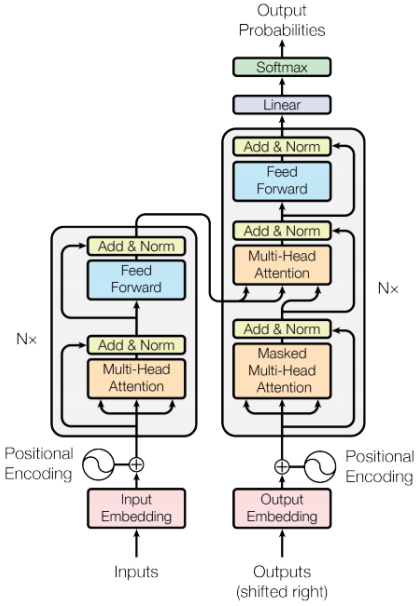

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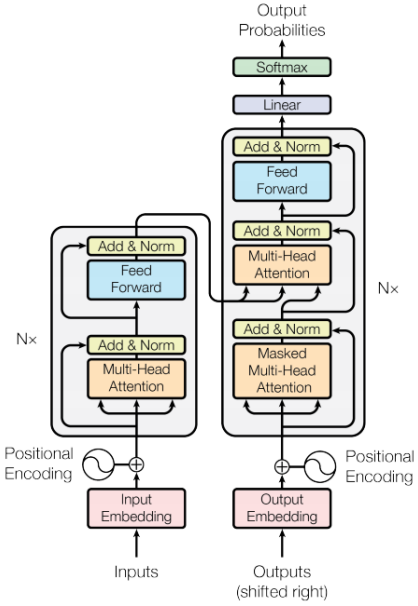

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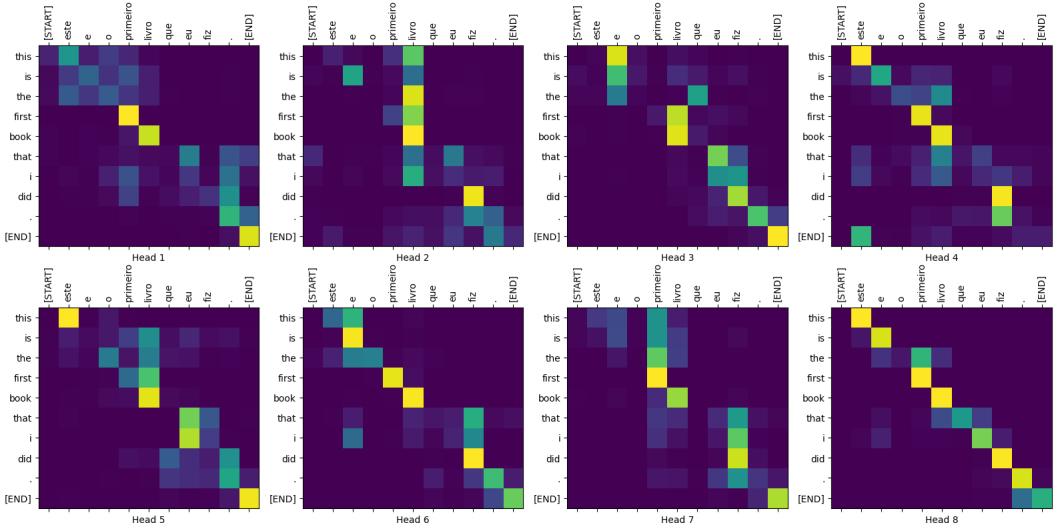

Based on https://www.tensorflow.org/text/tutorials/transformer

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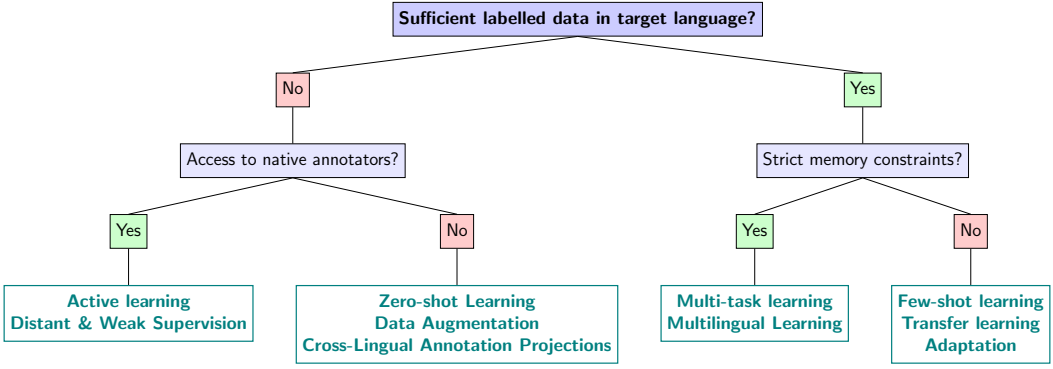

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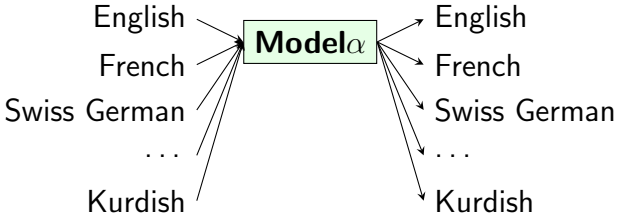

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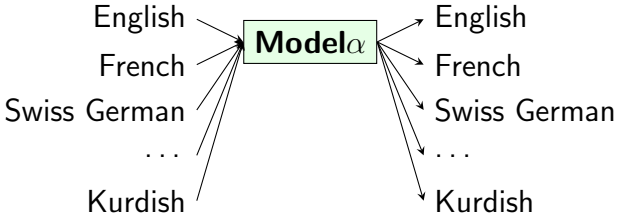

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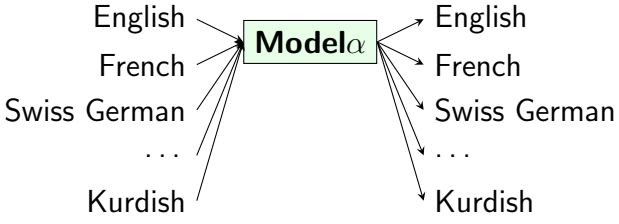

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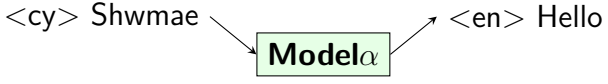

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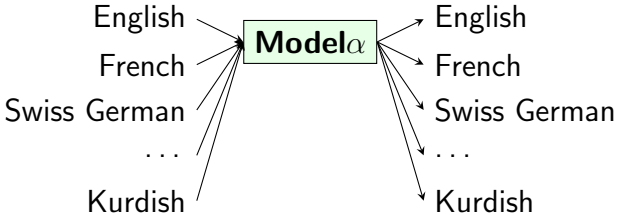

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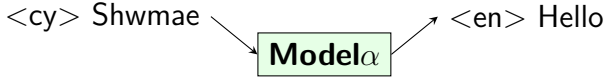

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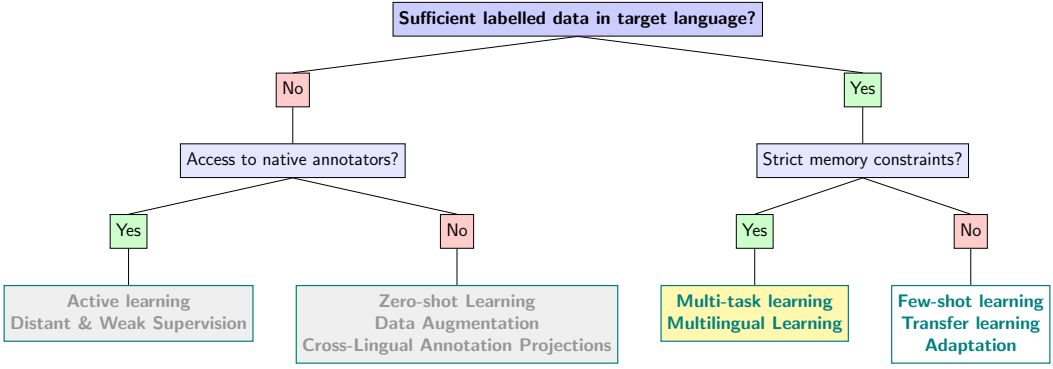

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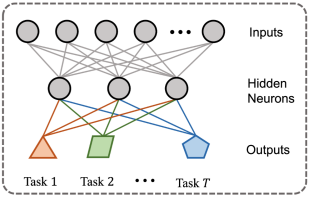

Multi-task learning framework (Yu et al., 2024)

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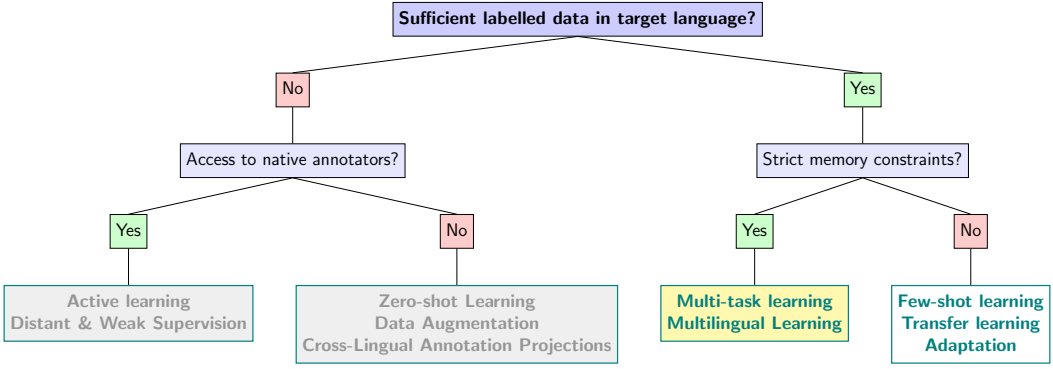

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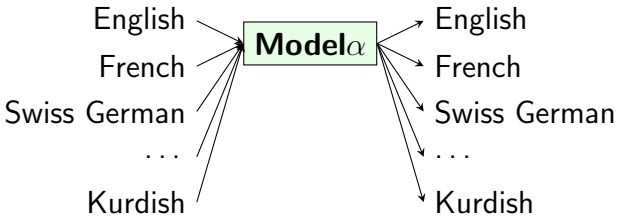

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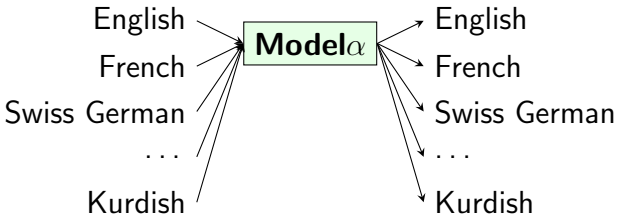

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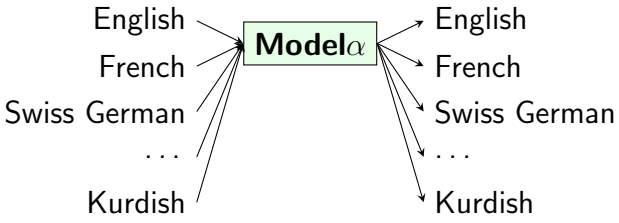

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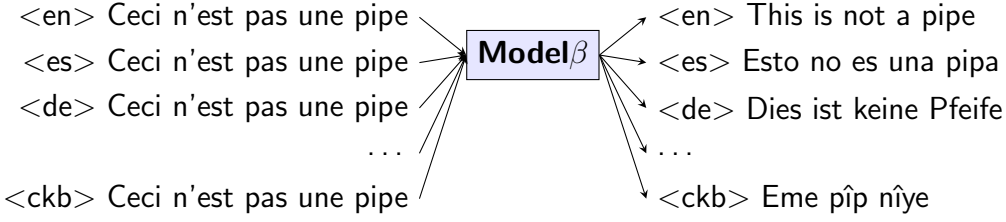

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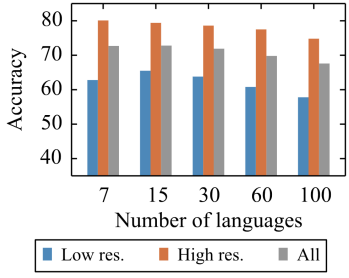

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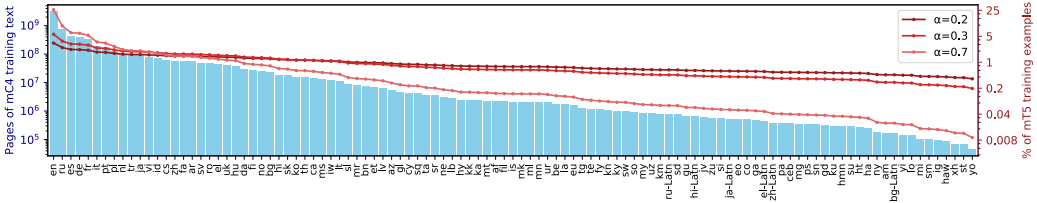

Vocabulary sampling in mT5 (Xue et al., 2020)

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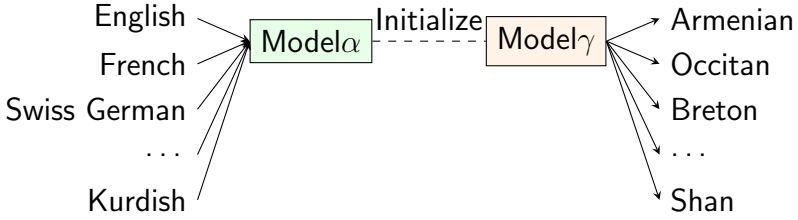

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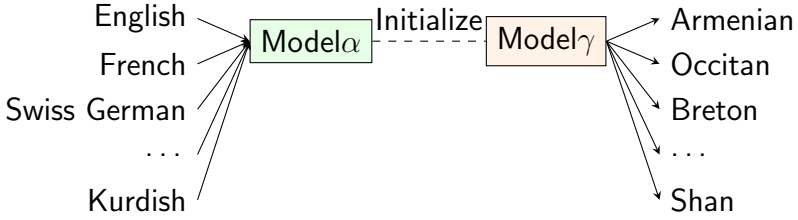

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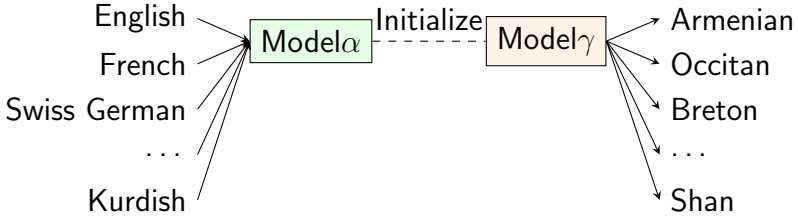

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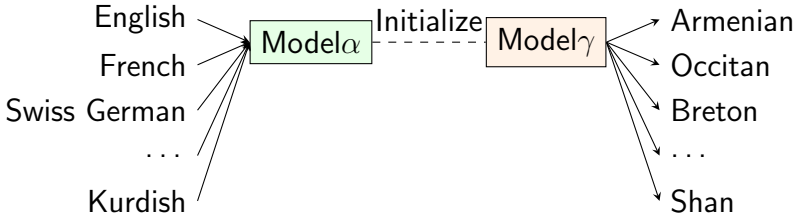

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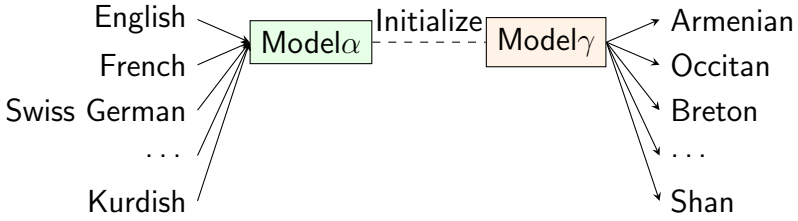

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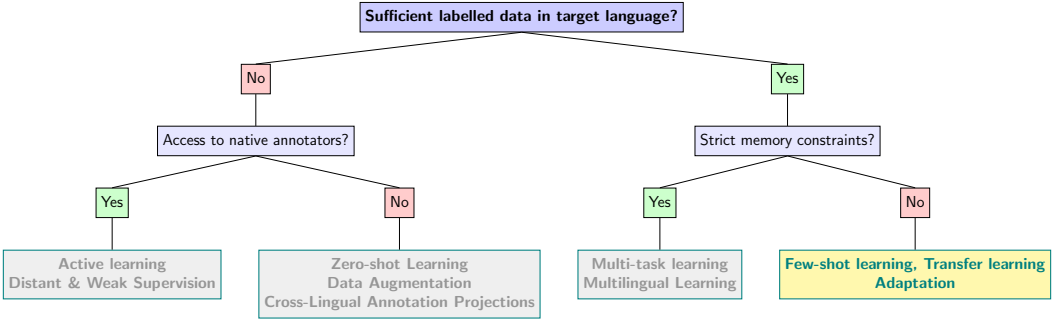

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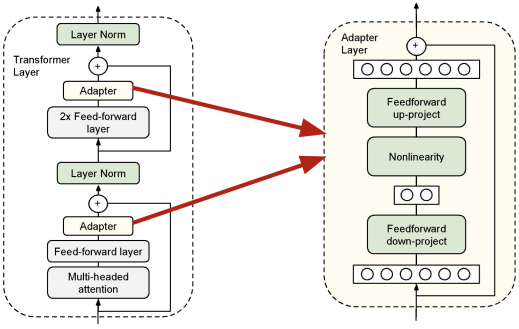

"Parameter-Efficient Transfer Learning for NLP." Houslby et al. 2019.

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- Can be used for multitask or multi-lingual learning

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- When fine-tuning a pre-trained model on a new task or language, it may **forget** what it previously learned $\rightarrow$ catastrophic forgetting

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- The bottleneck is shifting from *models* to *data and evaluation*

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References

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