# Natural Language Processing for Low-Resource and Marginalized Language Varieties

## Pillar III: Evaluation

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Adapted with thanks from Zdeněk Žabokrtský's "Evaluation measures in NLP" (NPFL124, Charles University)

# Recap

# NLP Framework

- Pillar I on Data: How to collect data?

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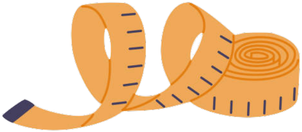
- Pillar II on Learning: How to learn a model?

# NLP Framework

- Pillar I on Data: How to collect data?
- Pillar II on Learning: How to learn a model?
- **Pillar III on Evaluation: How do we know whether our systems actually work?**



# Evaluation in NLP

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- Evaluation requires two things:
  - **Evaluation metrics** $\rightarrow$ what to measure
  - **Evaluation data** $\rightarrow$ what to measure on

# Automatic vs. manual evaluation

**Manual (human) evaluation:**

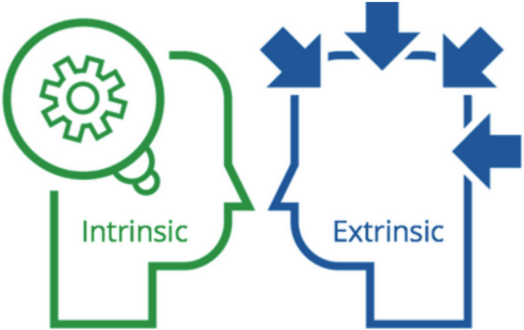
- Human judges assess system quality based on defined criteria
- Necessary when gold standards are hard to define (e.g., low inter-annotator agreement)

**Automatic evaluation:**

- Compare system output against a gold standard
- Cost of producing gold data can be high, but evaluation is then cheaply repeatable

# Intrinsic vs. extrinsic evaluation

- Intrinsic evaluation:



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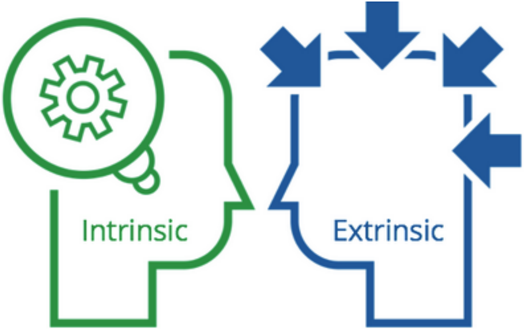

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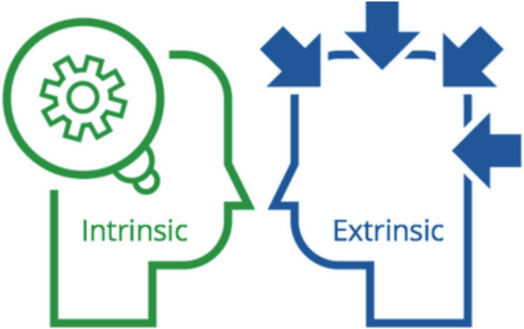

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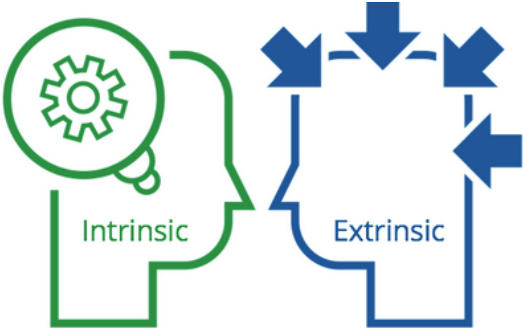

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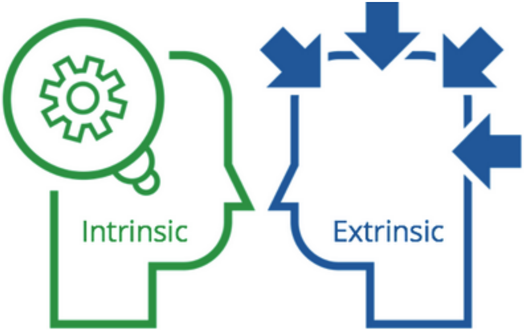

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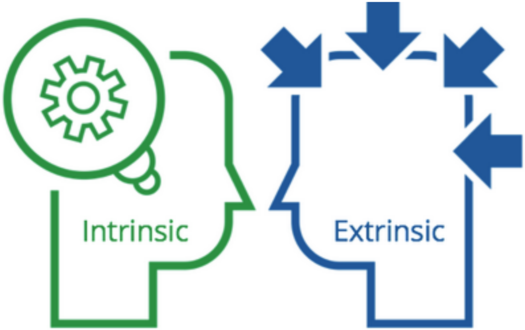
  - Example: does better POS tagging improve downstream MT quality?



# The naive experiment loop

The simplest approach:

1. Train a model on training data
2. Evaluate on evaluation data
3. Improve the model
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**What's wrong with this?**

The more iterations you run, the more the evaluation data effectively becomes part of your training signal

# A better data division

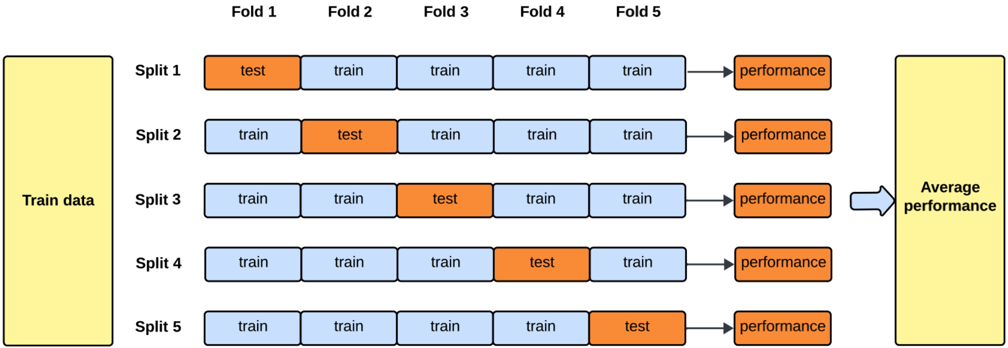
- Divide your data into **three** portions:
  - **Training data**: for model learning
  - **Development data** (devset / devtest): for tuning and iterative evaluation
  - **Test data** (etest): to be used *only once* for final evaluation
- Sometimes even more splits are needed (e.g., for hyperparameter selection)

When data is extremely scarce, even a three-way split may leave each portion too small to be reliable

# K-fold cross-validation

Especially useful when data is very small:

1. Partition data into $K$ roughly equal subsets (typically $K = 10$)
2. For each fold: train on $K - 1$ subsets, test on the remaining one
3. Average the $K$ results



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- Assumption: all errors are equally severe. Is that realistic?

# When accuracy is not enough

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Accuracy works well when:

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- The system gives exactly one answer per instance
- All errors are equally wrong
- But what if these assumptions don't hold? $\Rightarrow$ **precision** and **recall**

# Precision and recall

- **Precision**: when the system gives a prediction, how often is it right?

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- **Recall**: what proportion of all correct answers does the system find?

$$\text{recall} = \frac{\text{correct answers given}}{\text{all possible correct answers}} = \frac{TP}{TP + FN}$$

# F-measure

**F-measure** = weighted harmonic mean of precision (P) and recall (R):

$$F_\beta = \frac{(\beta^2 + 1) \cdot P \cdot R}{\beta^2 \cdot P + R}$$

Most commonly, equal weighting ($\beta = 1$):

$$F_1 = \frac{2 \cdot P \cdot R}{P + R}$$

- Balances the trade-off between precision and recall
- $\beta > 1$ favors recall; $\beta < 1$ favors precision

# Exercise: Precision, Recall, F1

A sentiment classifier labels movie reviews as **positive** or **negative**.

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$$\text{Accuracy} = \frac{\text{correctly predicted instances}}{\text{all instances}} = \frac{7}{10} = 70\%$$

# Word Error Rate (WER)

A common metric for speech recognition:

$$\text{WER} = \frac{S + D + I}{S + D + C}$$

where:

- $S$ = substituted words
- $D$ = deleted words
- $I$ = inserted words
- $C$ = correct words

WER can be misleadingly high when transcription norms are unstable or when code-switching is present

# BLEU (Bilingual Evaluation Understudy) (Papineni et al., 2002)

A common metric for machine translation:

$$\text{BLEU} = BP \cdot \exp\left(\frac{1}{4}\sum_{n=1}^{4}\log p_n\right)$$

$$BP = \min\left(1, \exp\left(1 - \frac{r}{c}\right)\right)$$

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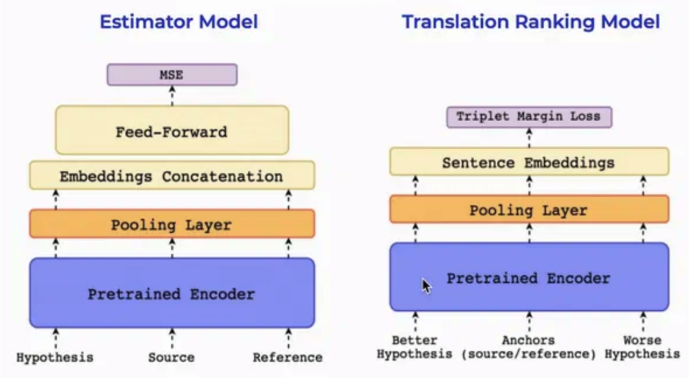
Limitations assumes a single reference is representative; struggles with morphologically rich languages and free word order

# Trainable Metrics: COMET (Rei et al., 2020)

- Unlike BLEU, which relies on surface-level $n$-gram overlap, **COMET** is a learned metric that uses a multilingual pre-trained encoder (e.g., XLM-R) to predict human quality judgments
- Trained on human evaluation data (e.g., direct assessments), it captures semantic similarity beyond lexical matching



# Evaluation as trade-off

Complex evaluation metrics are often a compromise between competing criteria:

- **F-measure**: precision vs. recall
- **BLEU**: $n$-gram precision vs. brevity penalty
- **Manual MT evaluation**: fluency vs. adequacy
- **COMET**: semantic similarity vs. fidelity to human judgments

There is no single "correct" metric $\rightarrow$ the choice depends on the task, the language, and the application context

# Interpreting Results

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  - **Lower bound**: performance of a baseline (a simple or trivial system)
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- The range 0–100% does not mean every value in that interval is reasonable

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- GPT-4 in a zero-shot setup
- Intermediate solutions (e.g., unigram model for POS tagging: $\arg\max P(\text{tag} \mid \text{word})$)
- The previous state-of-the-art result

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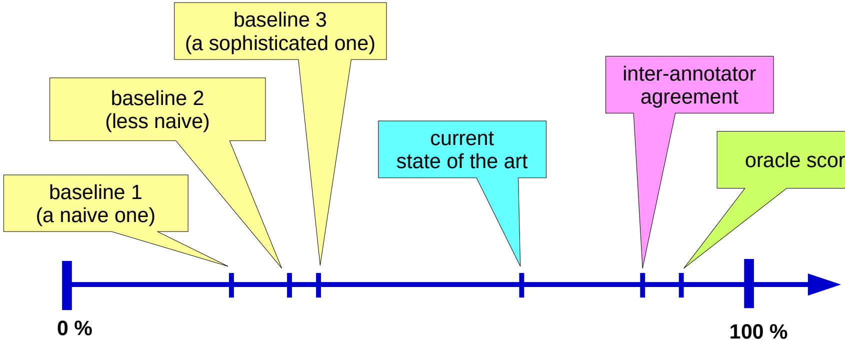
**Example**: oracle in POS tagging:

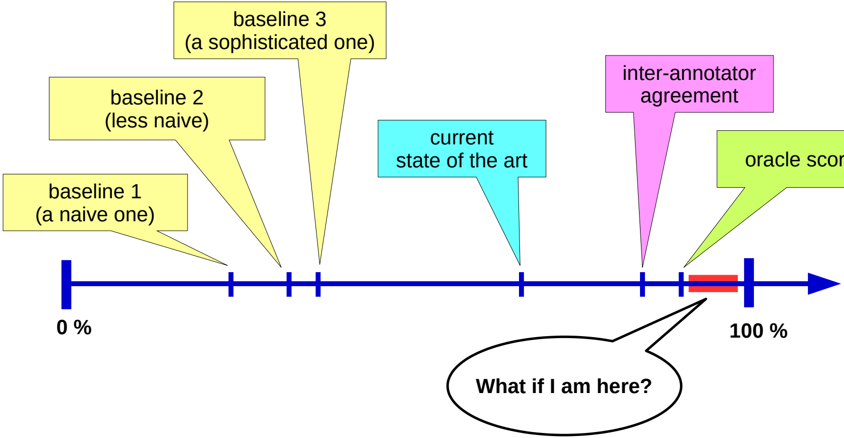
- Collect all possible POS tags per word from an annotated corpus
- On test data, select the correct tag whenever it appears in the candidate set

# Evaluation in context

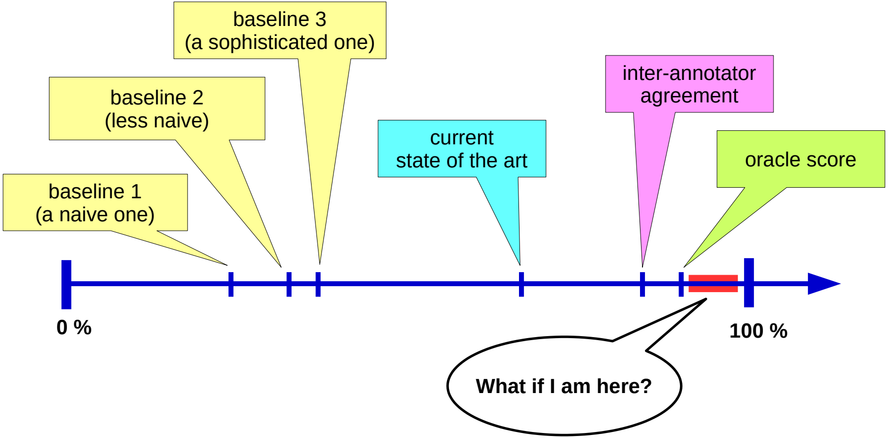



Always situate your result on a scale from baselines to oracle/IAA; a raw number alone is meaningless

# What if I'm here? Above the oracle

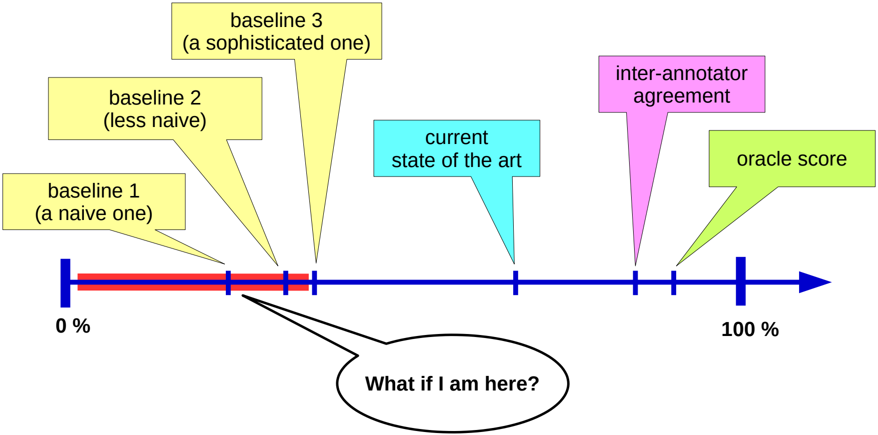


# What if I'm here? Above the oracle

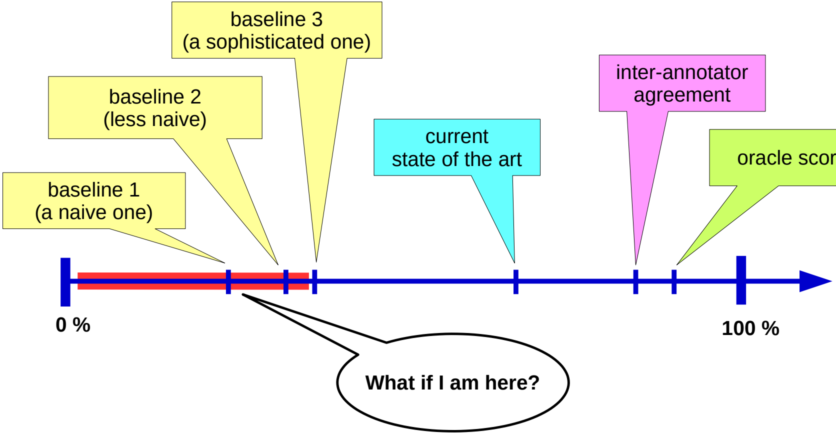



Outperforming an oracle is *impossible by definition*.
⇒ Search for a bug in your evaluation script.

# What if I'm here? Below all baselines

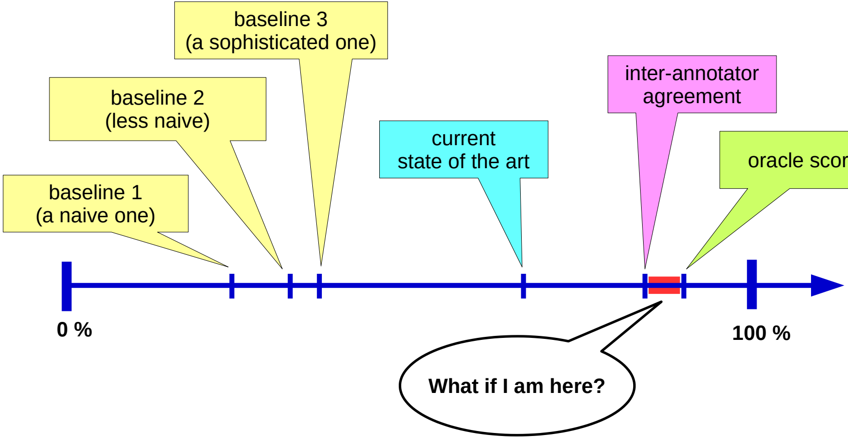


# What if I'm here? Below all baselines

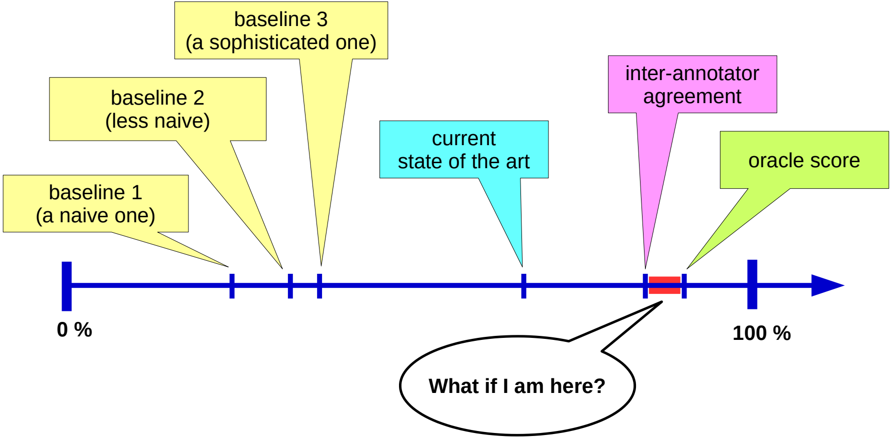



Something is likely wrong: model architecture, hyperparameters, underfitting/overfitting, or bugs. Apply standard ML diagnostics before publishing.

# What if I'm here? Above IAA

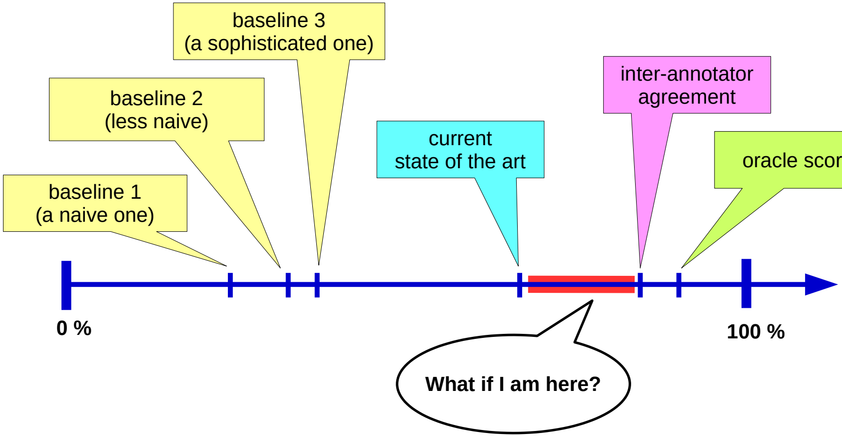


# What if I'm here? Above IAA




Possible but suspicious! In most NLP tasks, humans still outperform machines. Check for data leakage (e.g., mixing training and evaluation data).

# What if I'm here? New state of the art!



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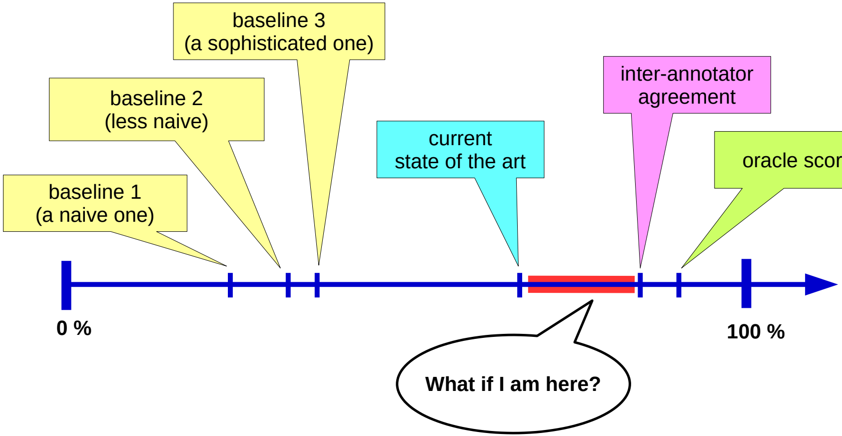
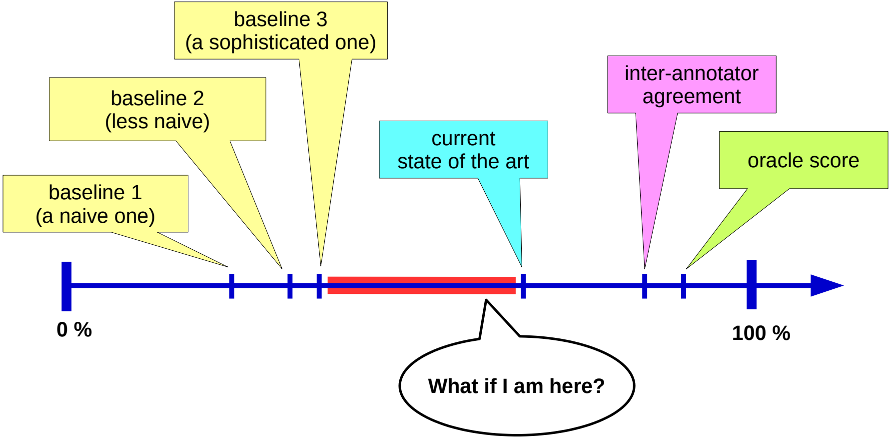



Congratulations! But double-check: is the setup fair? Did evaluation data leak into training? Did you evaluate too many times on the test set?

# What if I'm here? The most common outcome



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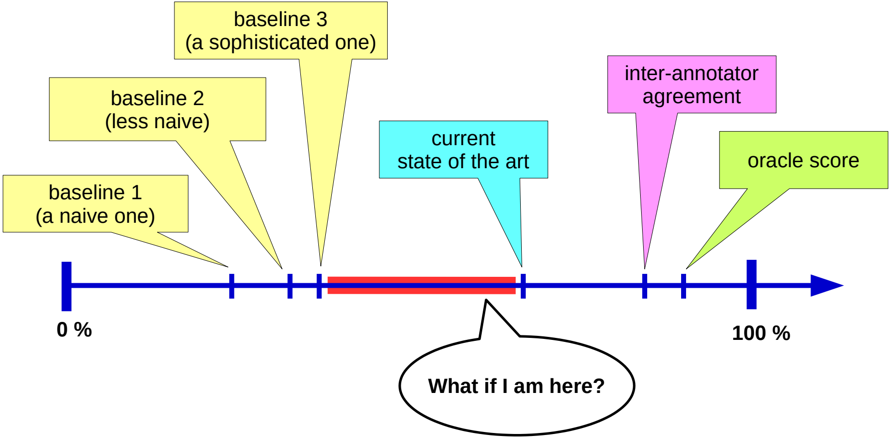


You beat the baselines but not the current SOTA; this is the most common result. Your approach may still be valuable for its speed, robustness in low-resource settings, or licensing.

# Annotation Quality and Agreement

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$\Rightarrow$ It is **essential** to quantify inter-annotator agreement (IAA)

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- Agreement by chance: $0.8 \times 0.85 + 0.2 \times 0.15 = 71\%$

# Cohen's Kappa

$$\kappa = \frac{P_a - P_e}{1 - P_e}$$

- $P_a$ = observed agreement (probability that annotators agree)
- $P_e$ = expected agreement by chance
- Scale from $-1$ to $+1$ (negative kappa is rare but possible)

Conventional interpretation:

- 0.40–0.59: weak agreement
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**Our example:** $\kappa = \frac{0.80-0.71}{1-0.71} = \frac{0.09}{0.29} = 0.31 \Rightarrow$ weak agreement, despite 80% raw agreement!

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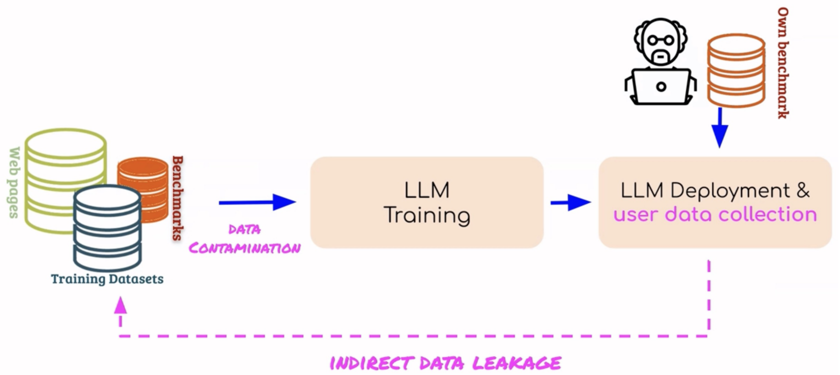
- **Statistical significance testing**: is the difference between two systems likely due to chance?
- Common tests: paired bootstrap resampling, approximate randomization
- Reporting confidence intervals helps readers judge whether improvements are meaningful

# Data Contamination

- **Data contamination** occurs when evaluation benchmark data appears in a model's training data



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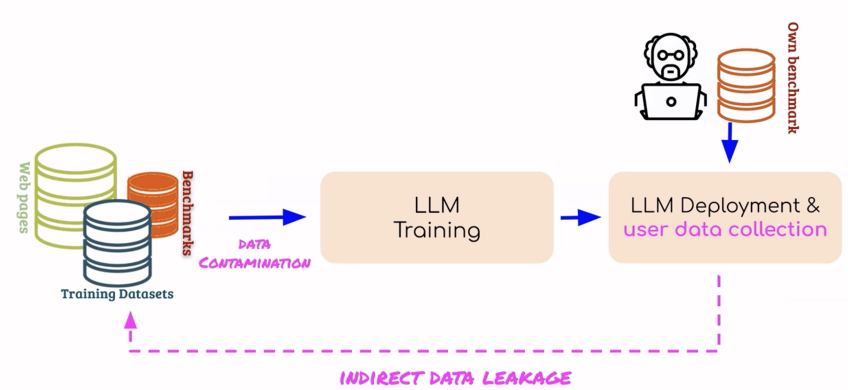
- Balloccu et al. (2024) reviewed recent papers evaluating closed-source LLMs: around 42% had leaked data!



# Takeaways

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- Evaluation is perhaps the most important role of data in NLP
- Every metric rests on assumptions; even plain accuracy assumes all errors are equally severe
- Results vary across datasets, genres, and languages; always anchor your results in a bigger picture (baselines, SOTA, oracle, IAA)
- Don't just report numbers. *Interpret* them!

# Reminders

**Seminar Presentations (starting next week):**

- Which paper do you present?

**Final Project (50% of assessment):**

- **Week 5** (next week): Problem Identification. Pick a language variety and a task.
- Week 8: Solution Proposal
- Week 14: Implementation & Presentation

# References

Several slides in this lecture are adapted from Zdeněk Žabokrtský's lecture on "Evaluation Measures in NLP" (NPFL070, Charles University, 2022), licensed under CC BY-SA.


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