Detecting
FINE-GRAINED Cross-Lingual Semantic Divergences
WITHOUT SUPERVISION
by Learning to Rank

Eleftheria Briakou & Marine Carpuat

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After the death of the dictator he is accused by Cassius of conspiring against Rome; he was subsequently put to death.

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Cross-lingual Semantic Divergences: Definition

Parallel sentences where source and target do not convey the exact same meaning

COARSE-GRAINED DIVERGENCES

- ✓ matter for NMT [Vyas et al., 2018]
- ✓ can be fixed for NMT [Pham et al., 2018]

FINE-GRAINED DIVERGENCES

- ✓ arise during translation [Zhai et al. 2018]
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- divergences vary in their granularity
- annotator agreement

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Parallel corpus: WikiMatrix

Key findings: Fine-grained distinctions…

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by learning to rank synthetic
divergences of varying granularity

Annotating cross-lingual semantic divergences

<u>Annotation Protocol</u>

Goal: encourage annotator's sensitivity to subtle meaning differences

Rationalized
English
FREnch
Semantic
Divergences

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REFRESD: Our annotation Protocol

Given an English-French WikiMatrix sentence-pair

She made a courtesy call to the Hawaiian Islands.

Il fait une escale aux îles Hawaï.

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SOME MEANING DIFFERENCE

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UNRELATED

distinct classes

REFRESD: Annotation findings

- Rationales improve annotator agreement

- Semantic divergences are frequent in REFreSD

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  Vyas et al.

  Krippendorf's α: 0.60 vs. 0.41 & 0.49

- Semantic divergences are frequent in REFRESD

  24% Unrelated

  40% Some meaning difference

  36% No meaning difference

REFRESD: Annotation findings

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  Krippendorf's α: 0.60

- Semantic divergences are frequent in REFRESD

  24% Unrelated
  40% Some meaning difference
  36% No meaning difference

Our hypothesis: parallel text often presents semantic divergences…

holds 64% of times in REFreSD

Predicting semantic divergences:
Problem definition

INPUT She made a courtesy call to the Hawaiian Islands.
Il fait une escale aux îles Hawaï.

OUTPUT EQUIVALENCE VS. DIVERGENCE

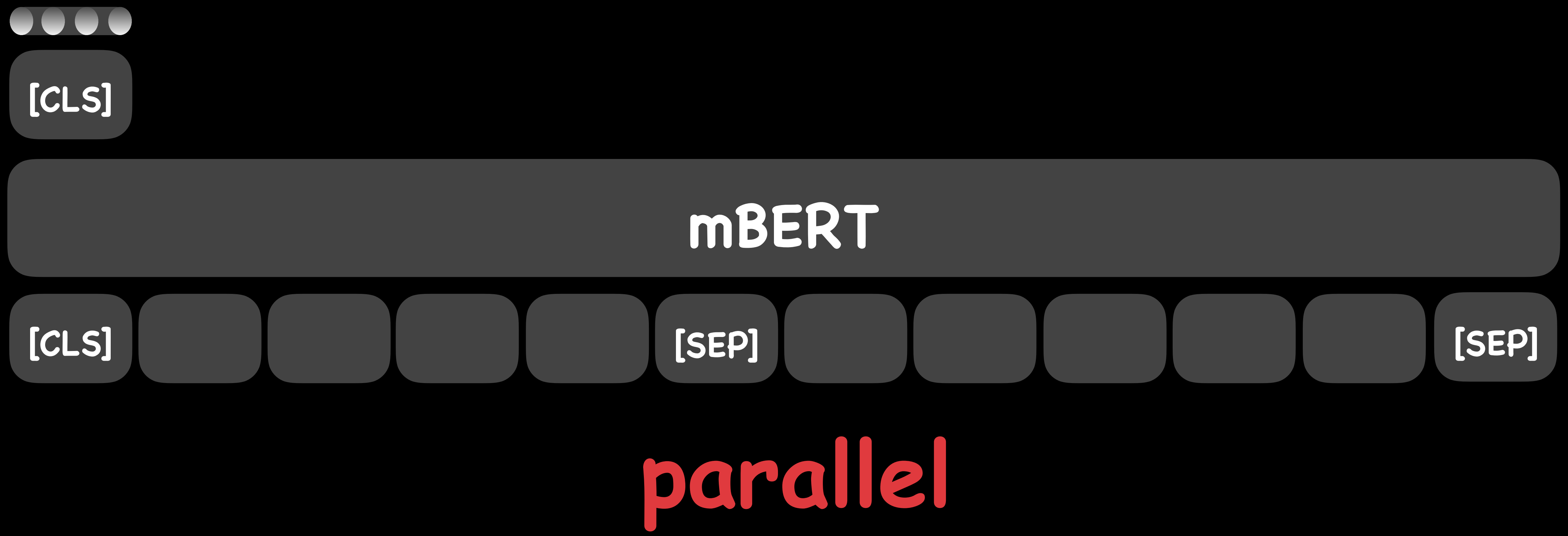
Predicting semantic divergences: **Challenges**

INPUT She made a courtesy call to the Hawaiian Islands.
Il fait une escale aux îles Hawaï.

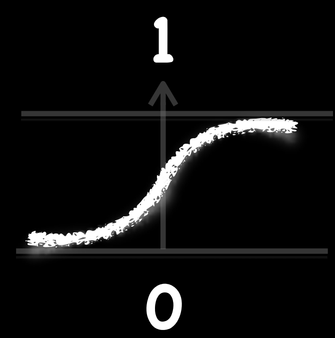
OUTPUT EQUIVALENCE VS. DIVERGENCE

✓ no human-annotated training data
✓ divergences can be fine-grained

Divergent mBERT



Divergent mBERT



F(parallel) $\longrightarrow$ probability of being equivalent

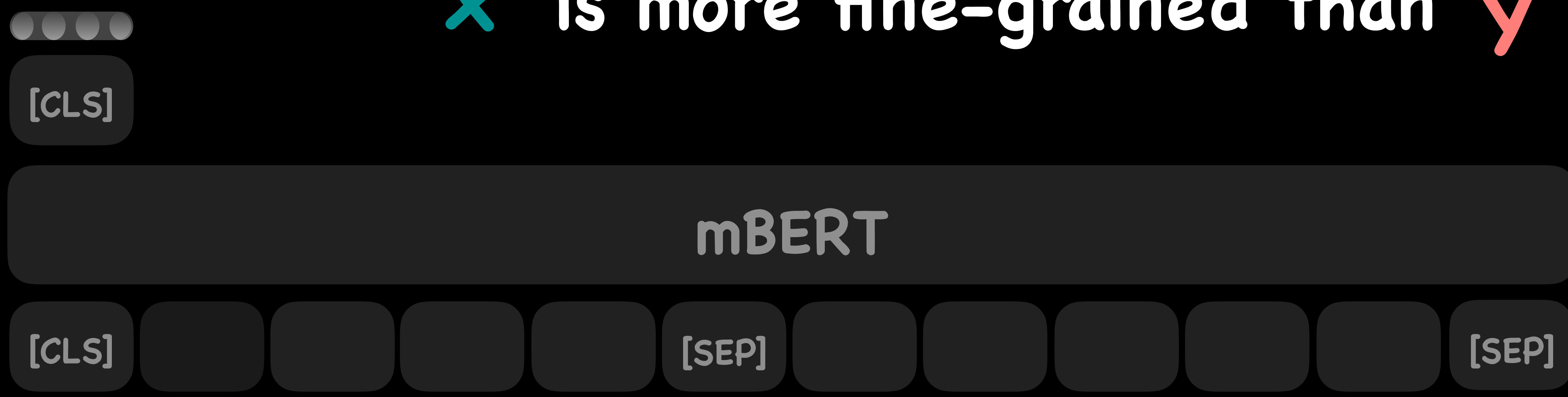
parallel

Divergent mBERT: Contrastive pairs

$$D = \{(x, y)\}$$

contrastive pair

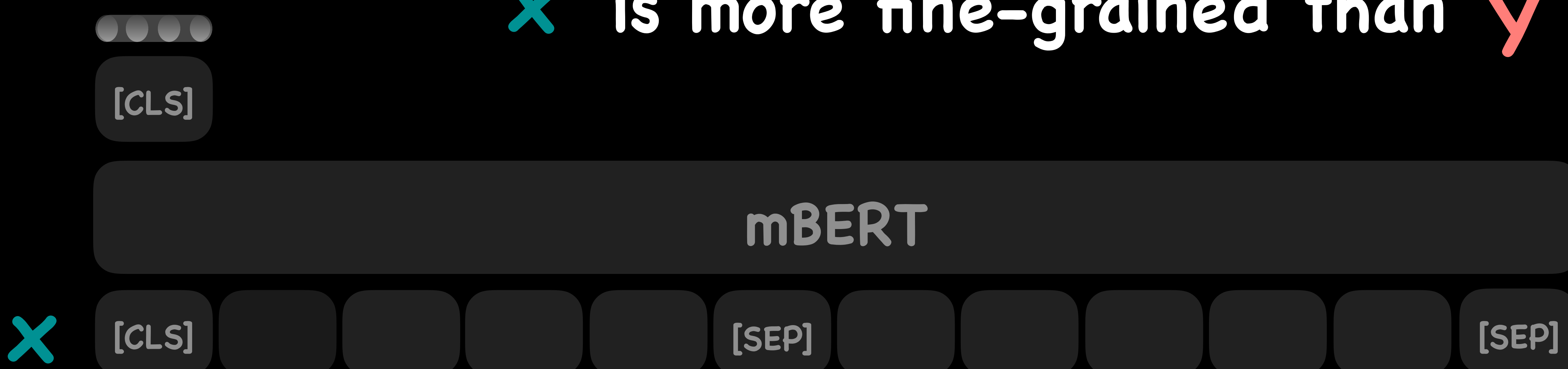
x is more fine-grained than y



Divergent mBERT: Contrastive pairs

$F(x)$

x is more fine-grained than y



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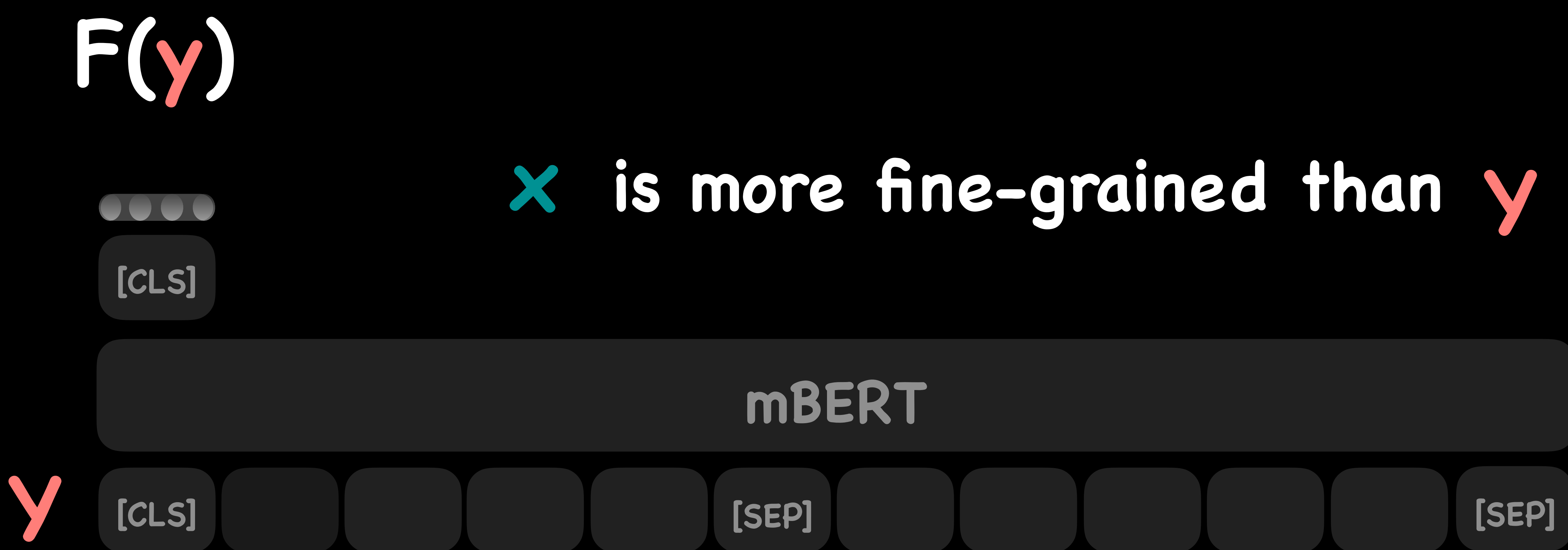
Divergent mBERT: Contrastive pairs



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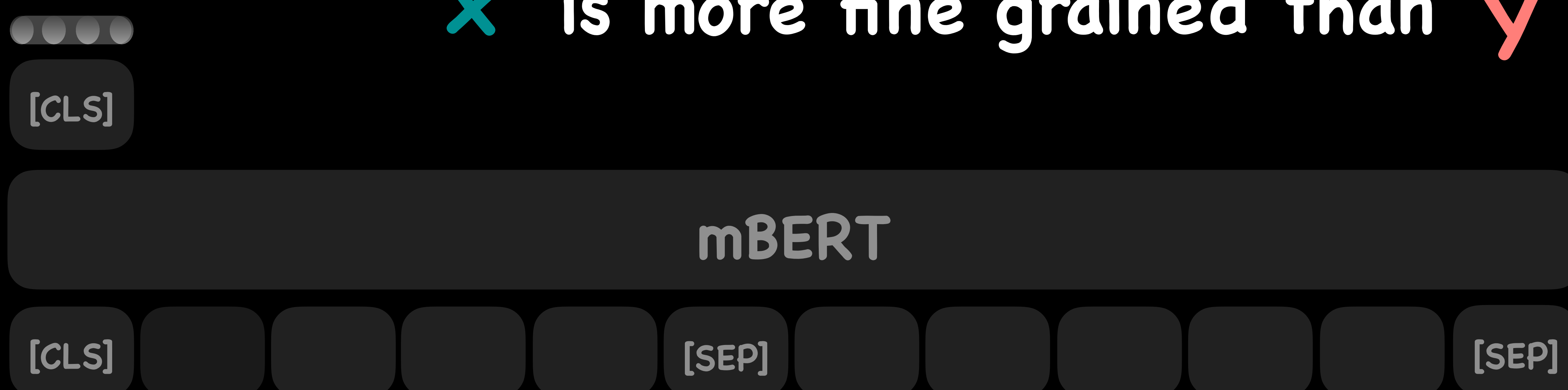
Divergent mBERT: Learning to rank contrastive pairs

$$\max\{0, \xi - F(x) - F(y)\}$$

x is more fine grained than y



$$D = \{(x, y)\}$$

Synthetic training data

Synthetic training data:
Seed equivalent

Now however one of them is suddenly asking your help and you can see from this how weak they are.

Maintenant cependant l'un d'eux vient soudainement demander votre aide et vous pouvez voir à quel point ils sont faibles

Synthetic training data:
Subtree Deletion

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Synthetic training data:
Phrase Replacement

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Now however one of them is absolutely fighting his policy and you can see from this how weak they are.

Maintenant cependant l'un d'eux vient soudainement demander votre aide et vous pouvez voir à quel point ils sont faibles

Synthetic training data:
Lexical Substitution

Now however one of them is suddenly asking your **help** and you can see from this how weak they are.

Maintenant cependant l'un d'eux vient soudainement demander votre **aide** et vous pouvez voir à quel point ils sont faibles

Synthetic training data:
Lexical Substitution

Now however one of them is suddenly asking your **mercy** and you can see from this how weak they are.

Maintenant cependant l'un d'eux vient soudainement demander votre **aide** et vous pouvez voir à quel point ils sont faibles

Contrastive pairs:
Divergences contrasts with specific seed

Lexical Substitution

Phrase Replacement

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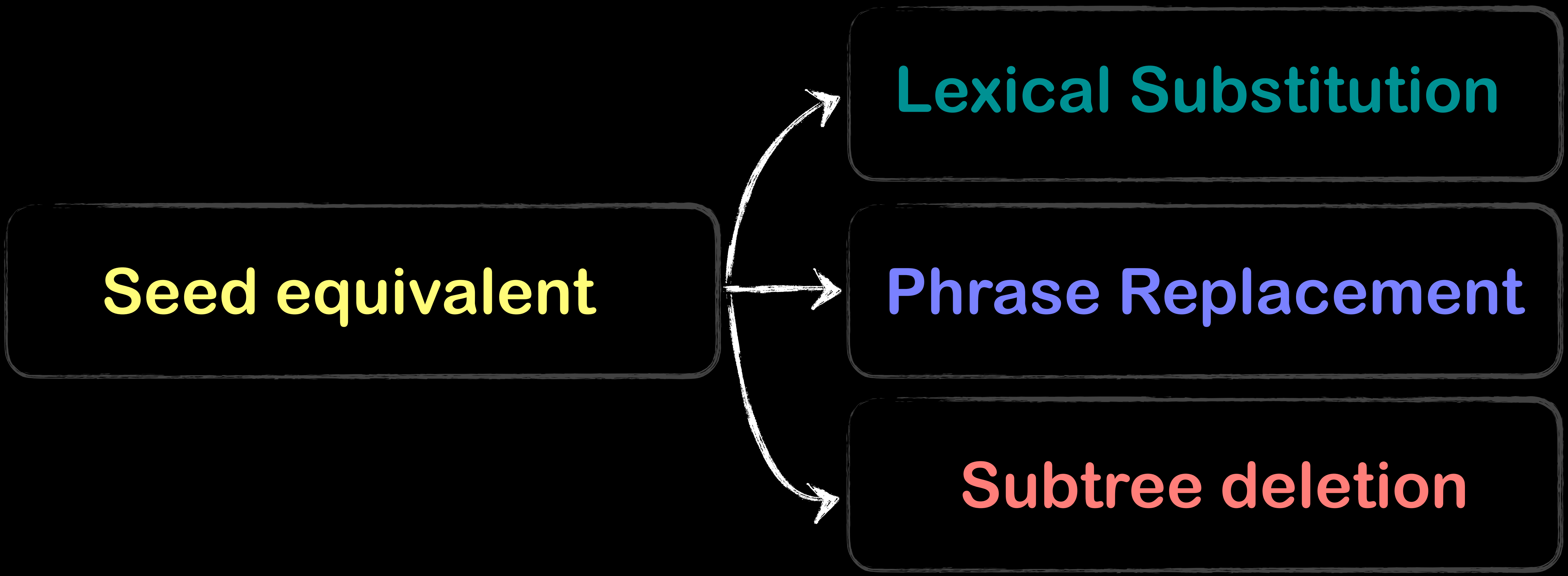
Contrastive pairs:
Divergences contrasts with specific seed



Learning to rank contrastive divergences: One type at a time

Seed equivalent > Lexical Substitution

Learning to rank contrastive divergences: One type at a time

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Rank contrastive divergences of increasing granularity

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Learning to rank contrastive divergences: Divergence ranking

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Seed equivalent	>	Lexical Substitution
Lexical Substitution	>	Phrase Replacement
Lexical Substitution	>	Subtree deletion

Binary divergence detection:
Evaluation on REFreSD

NO MEANING DIFFERENCE

SOME MEANING DIFFERENCE

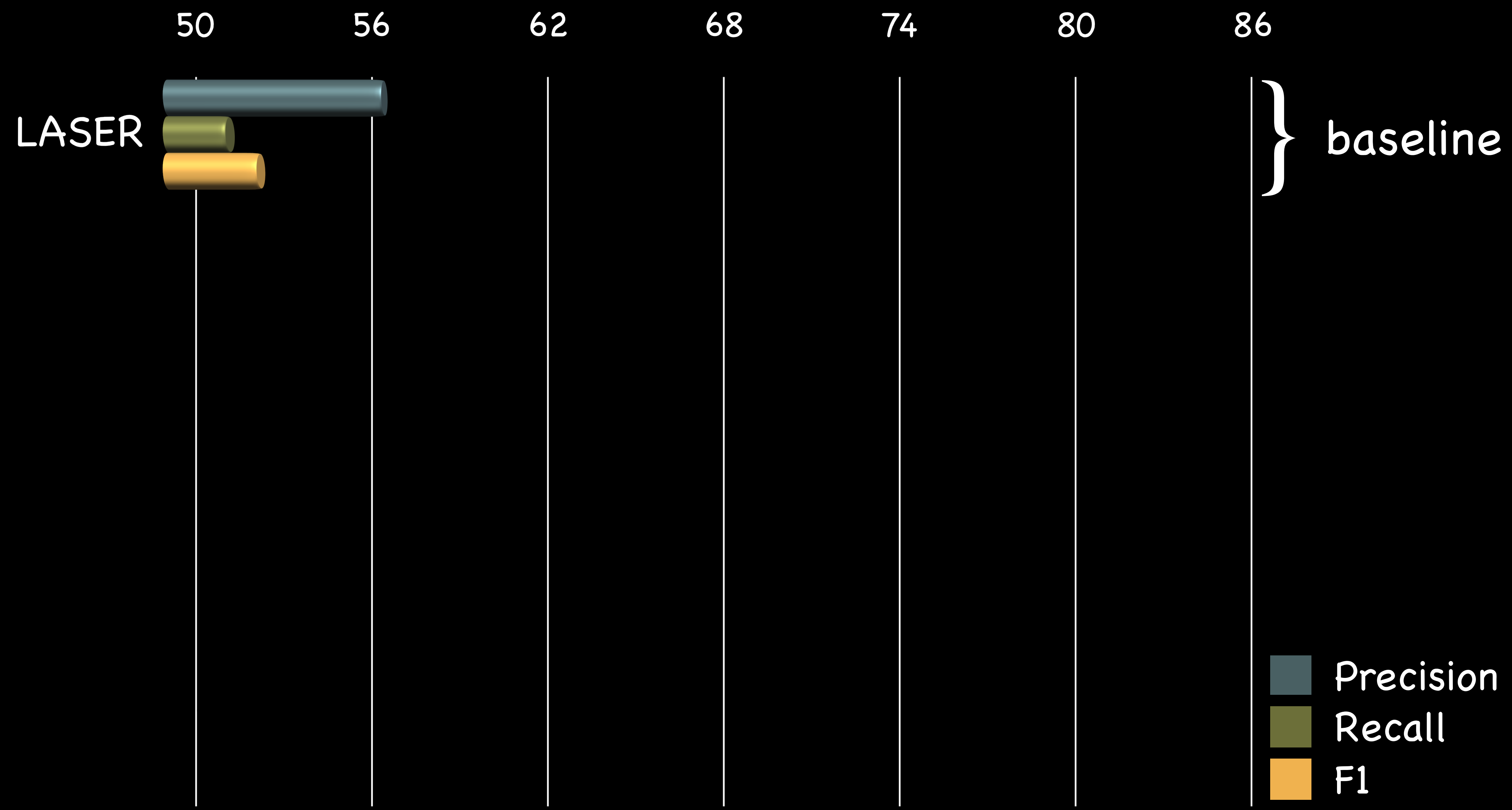
UNRELATED

Binary divergence detection:
Evaluation on REFRESD

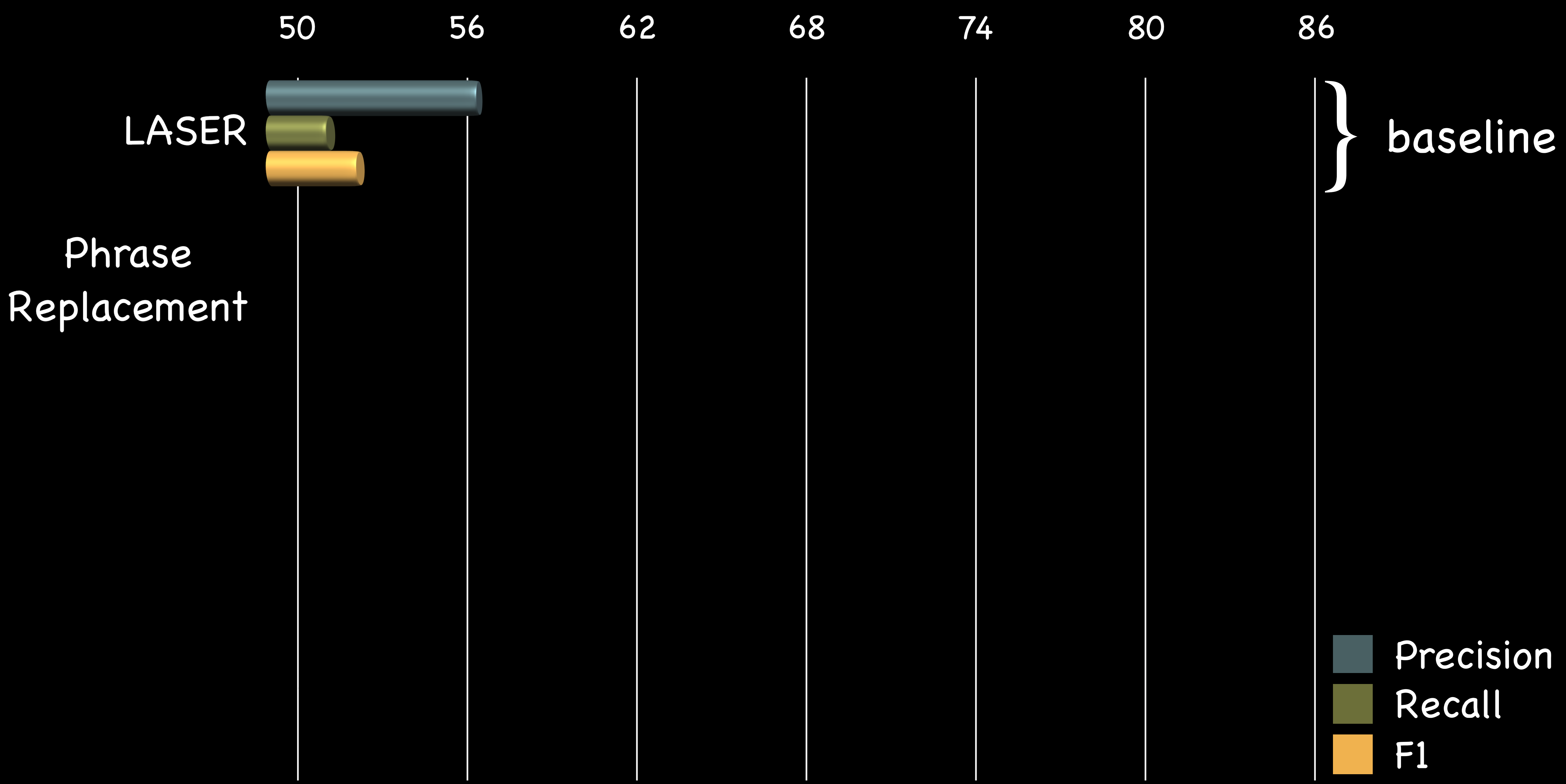
- NO MEANING DIFFERENCE — Equivalent
- SOME MEANING DIFFERENCE
- UNRELATED

Divergent

Binary divergence detection: LASER fails to detect divergences in REFRESD



Binary divergence detection: Divergent mBERT vs. LASER baseline



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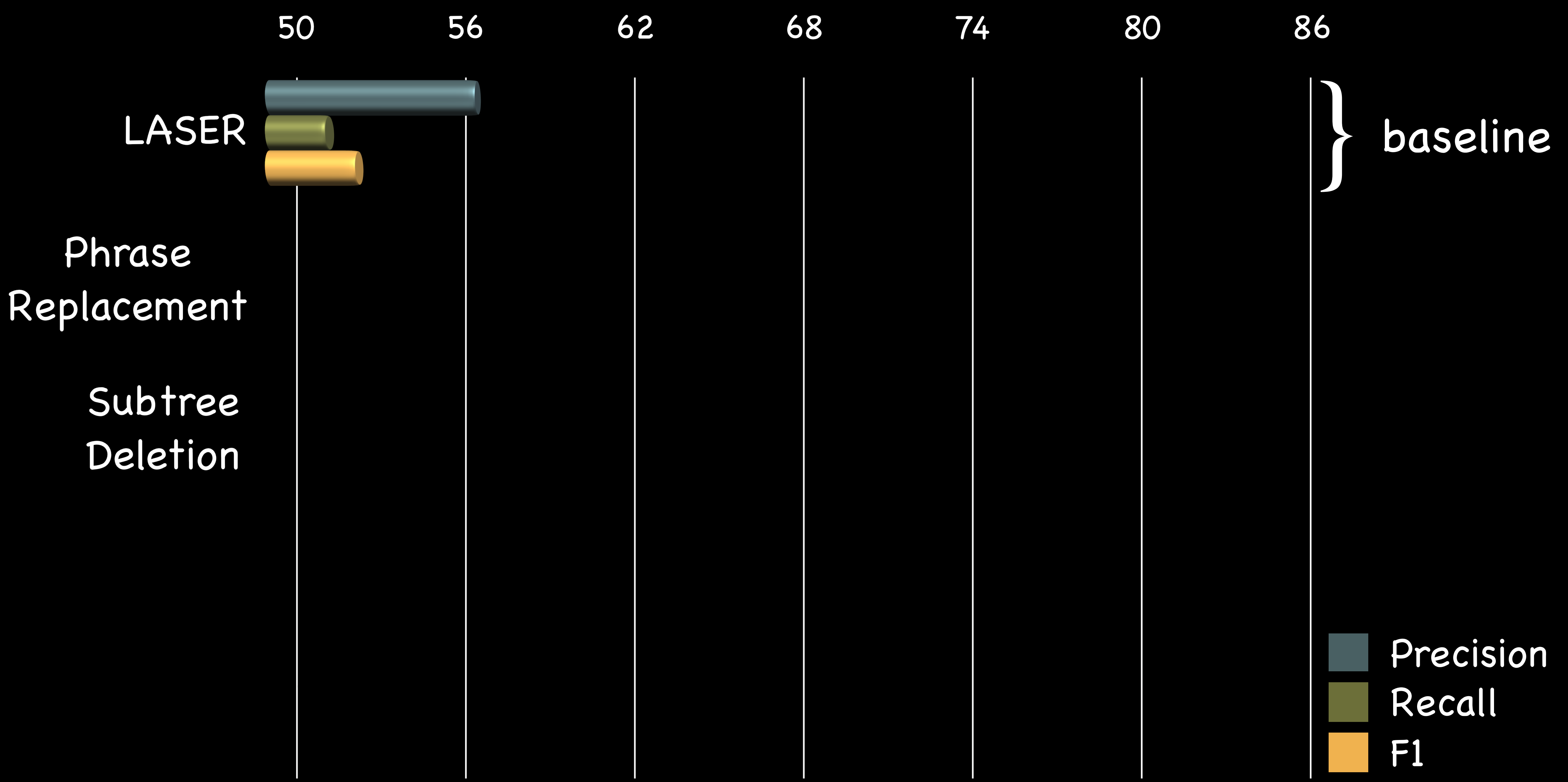

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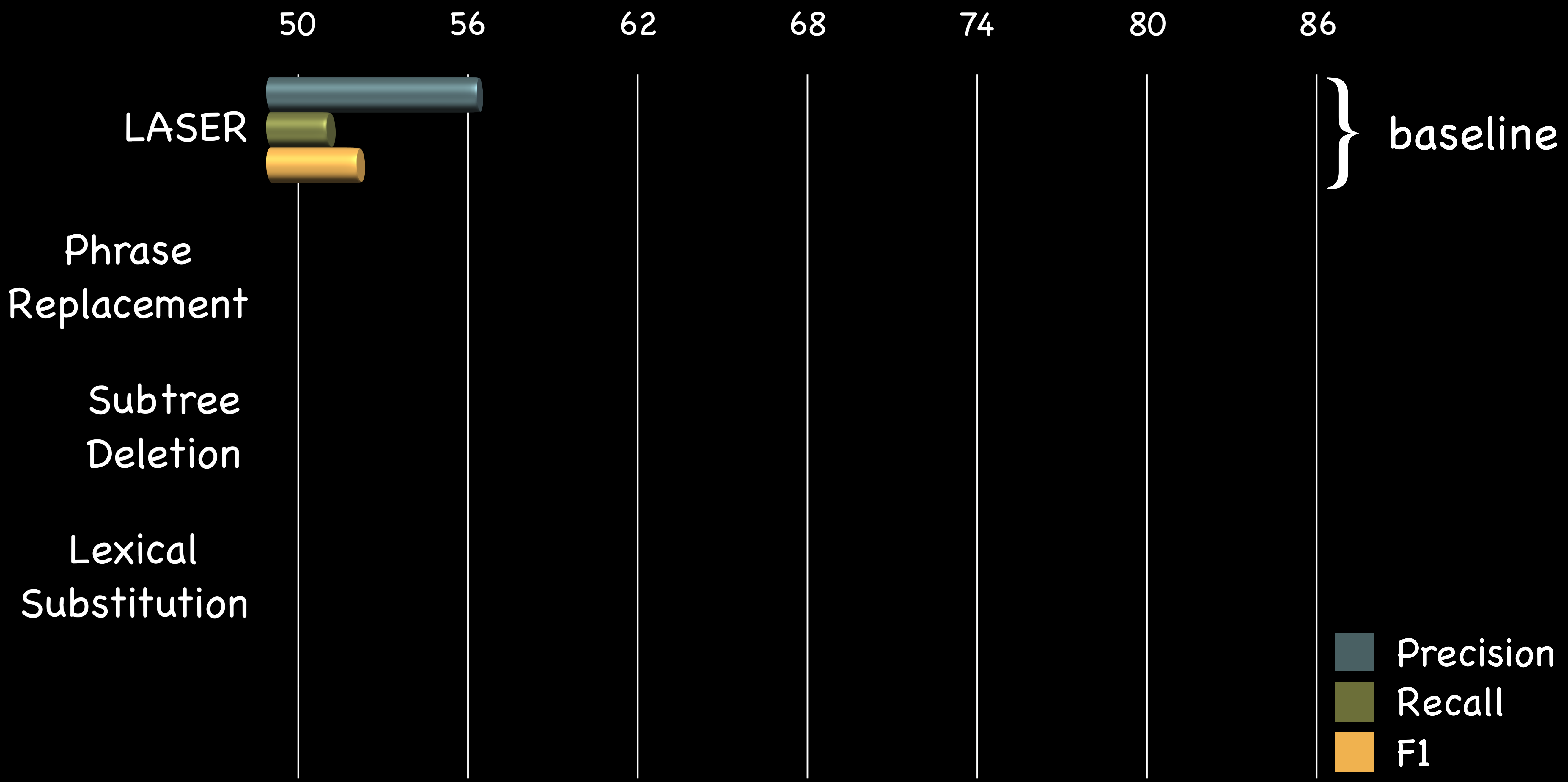
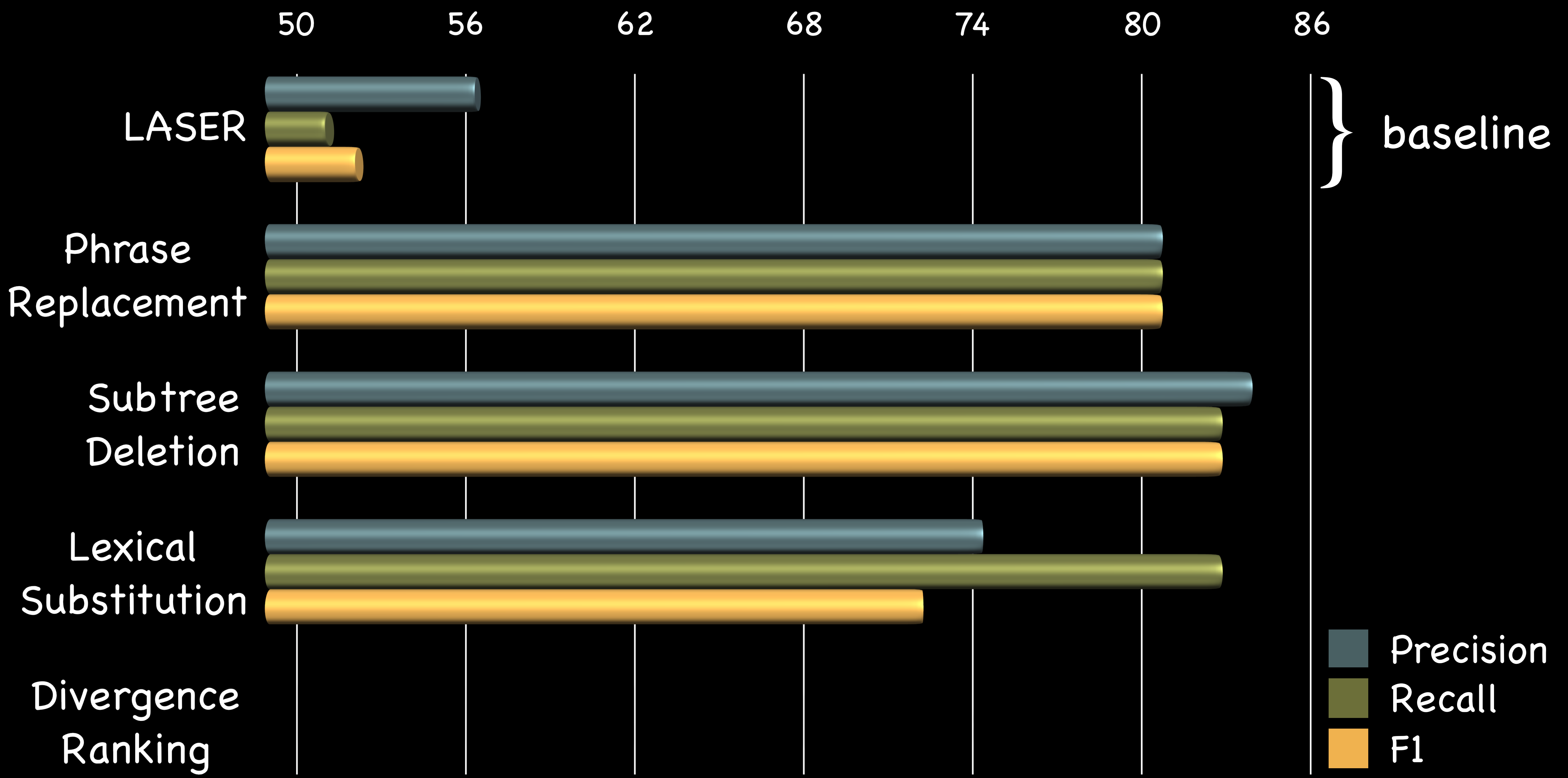
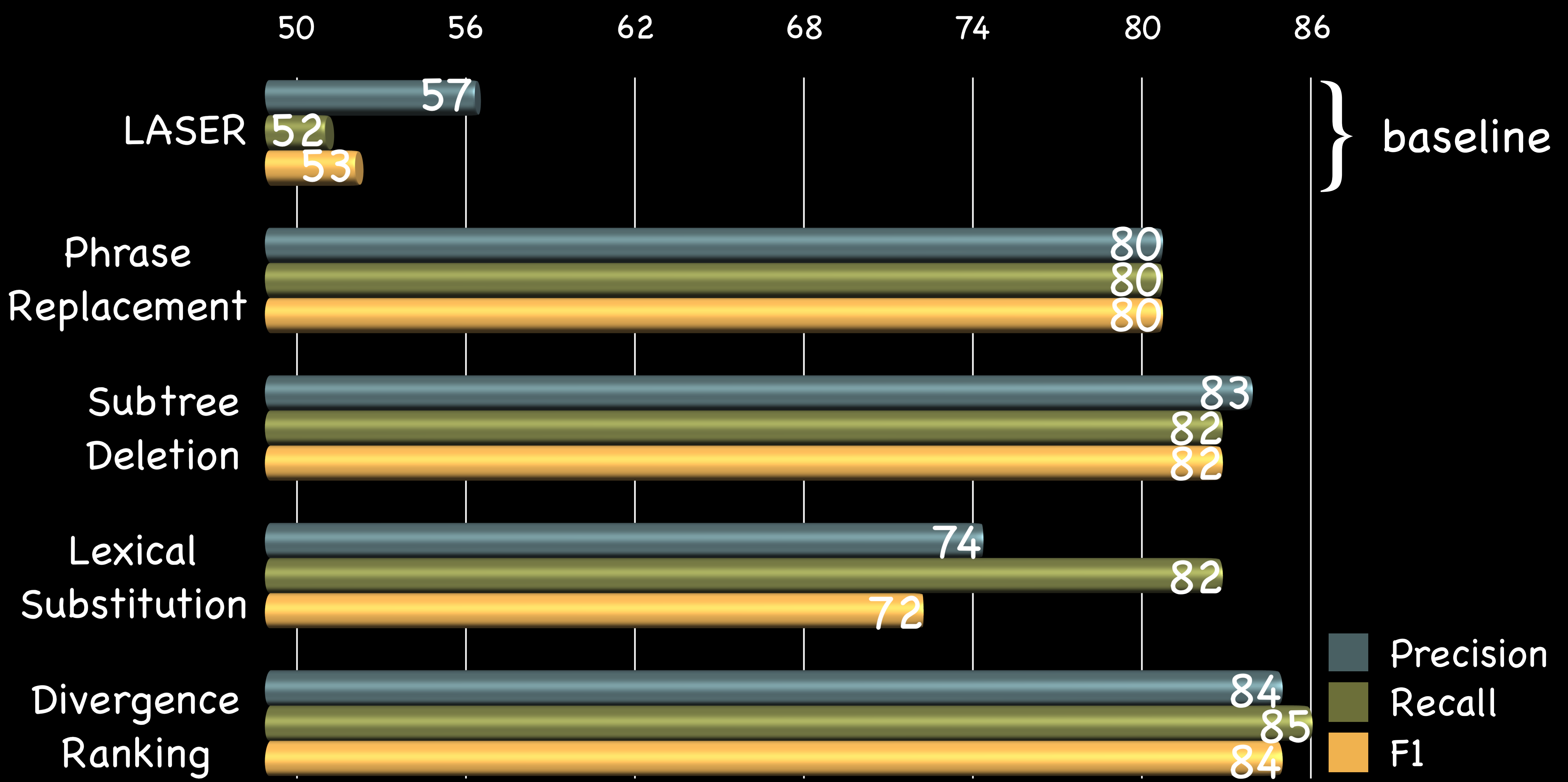


Binary divergence detection: Divergent mBERT outperforms LASER



Binary divergence detection: Divergence Ranking performs best across metrics



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Fine-grained distinctions…

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https://github.com/Elbria/xling-SemDiv