Data Selection
with
Cluster-Based Language Difference Models
and
Cynical Selection

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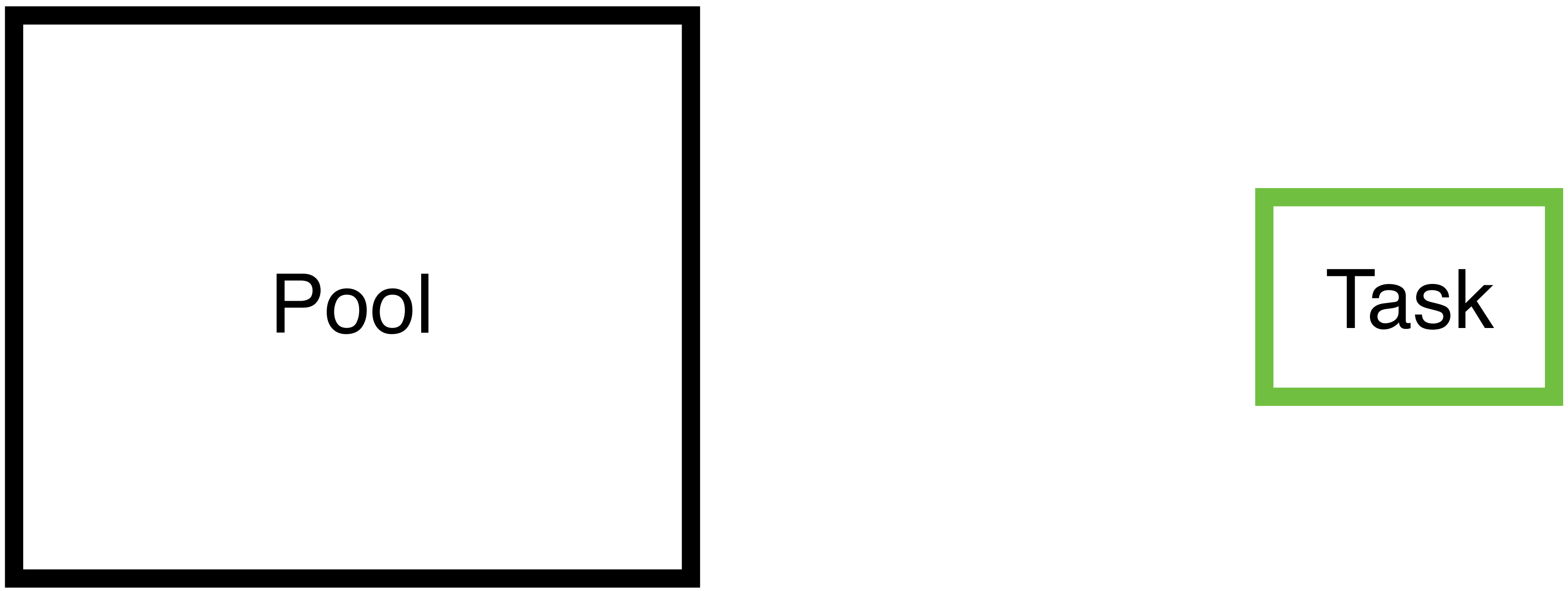
Domain Adaptation



Lots of data

Data I care about

Domain Adaptation

Pool

Lots of data

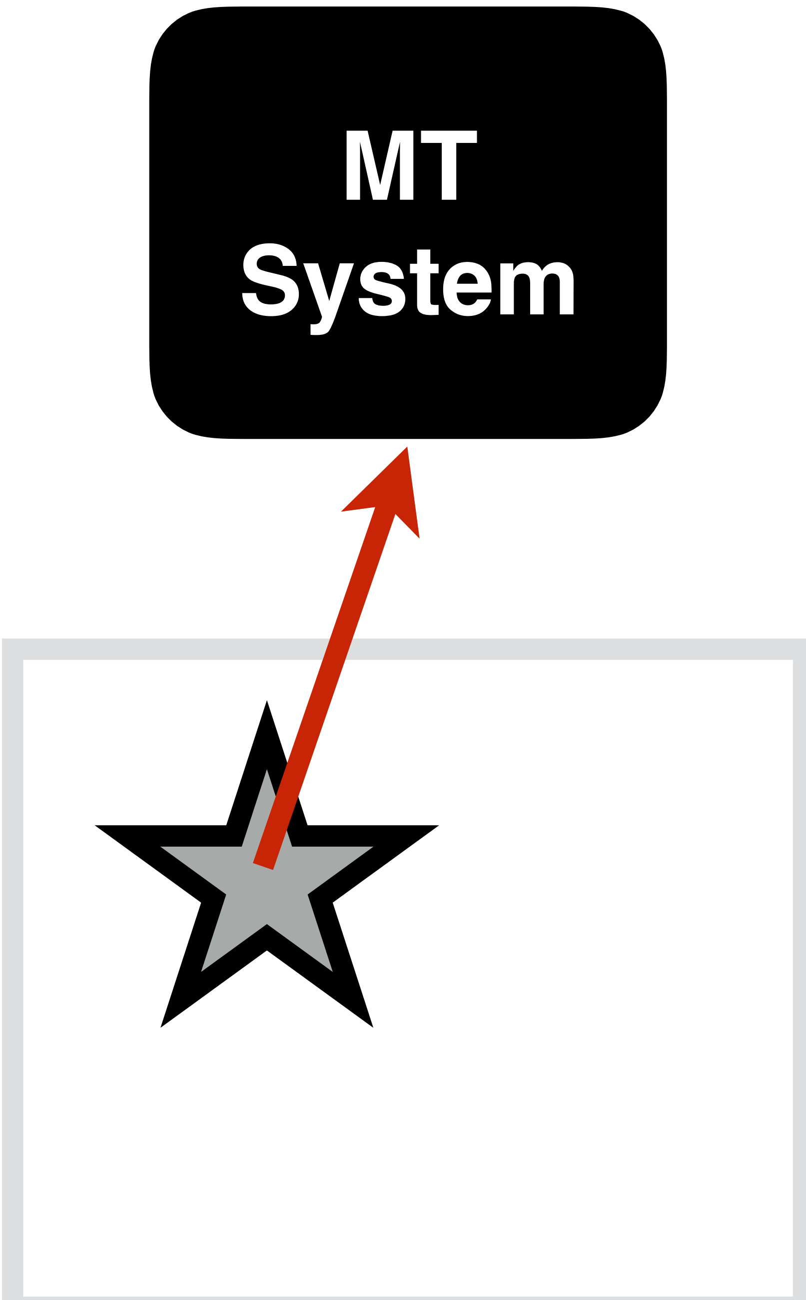
Task

Data I care about

Use this…

…for that

Data Selection



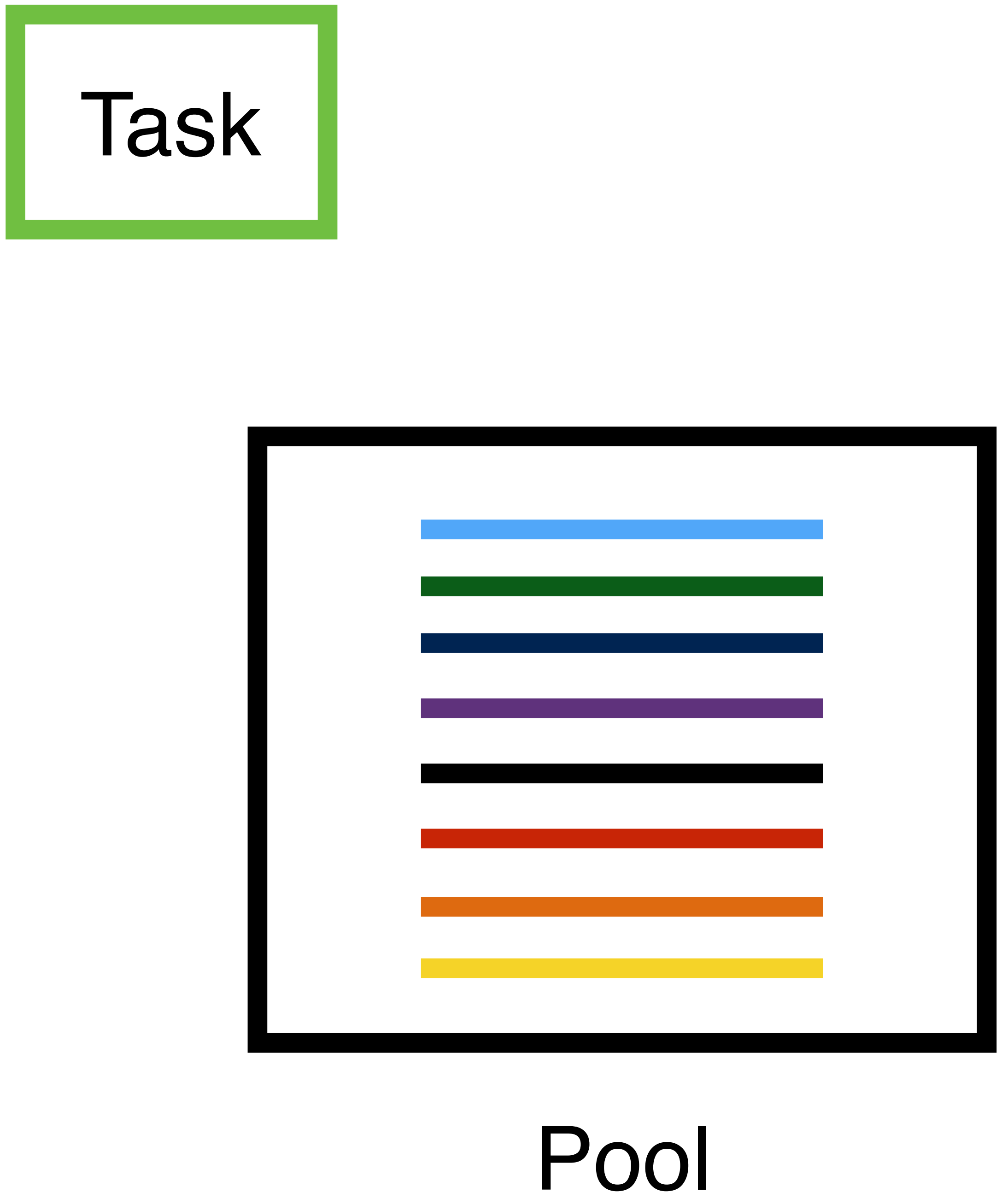
- Use same MT toolkit, with better input!
- Outdated: "There's no data like more data."

↓

There's no data like **relevant** data!

Data Selection Process

- Compute similarity of sentences in pool to the task corpus
- Sort pool sentences by score
- Select (keep) some
- Build task-specific MT system



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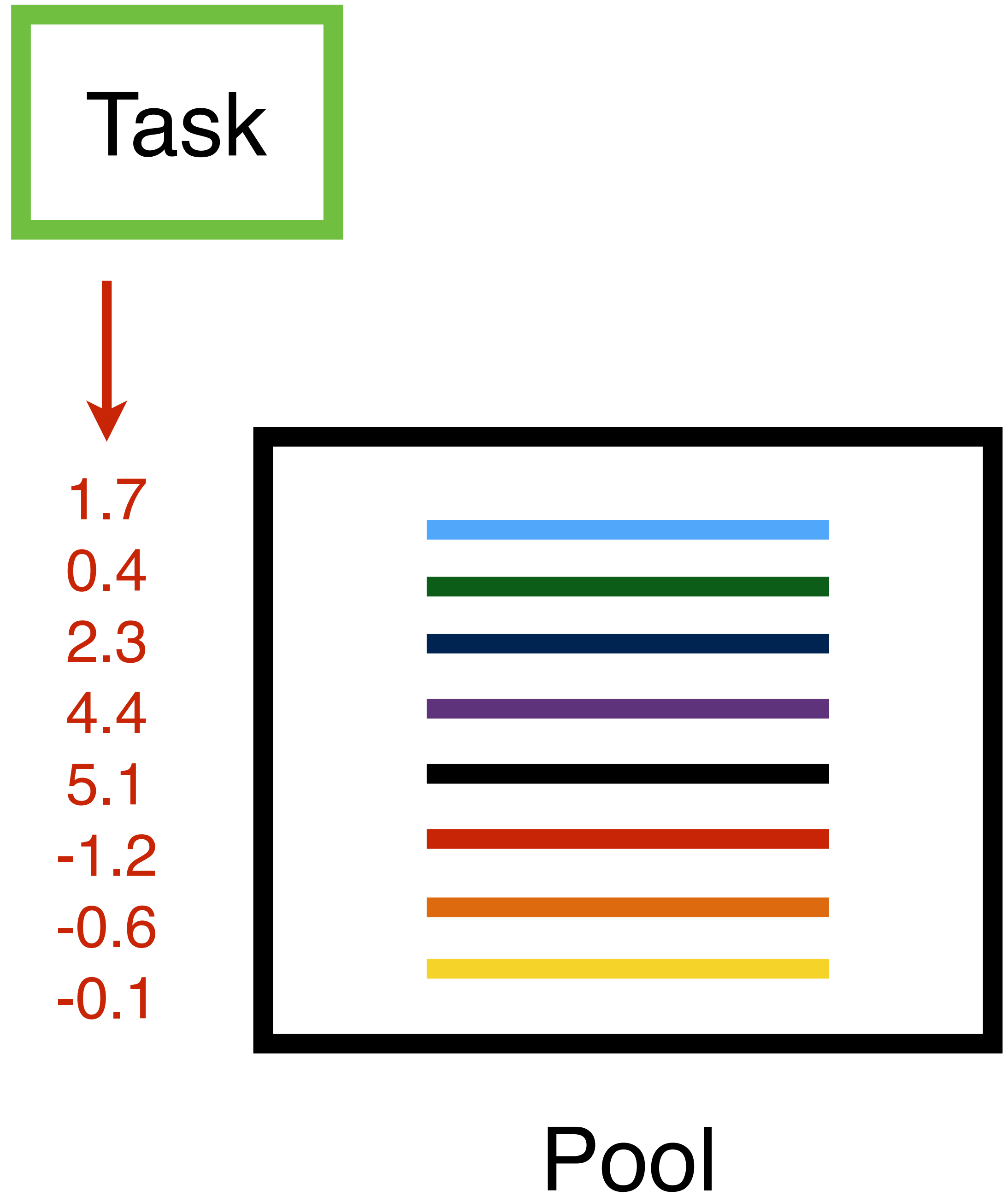

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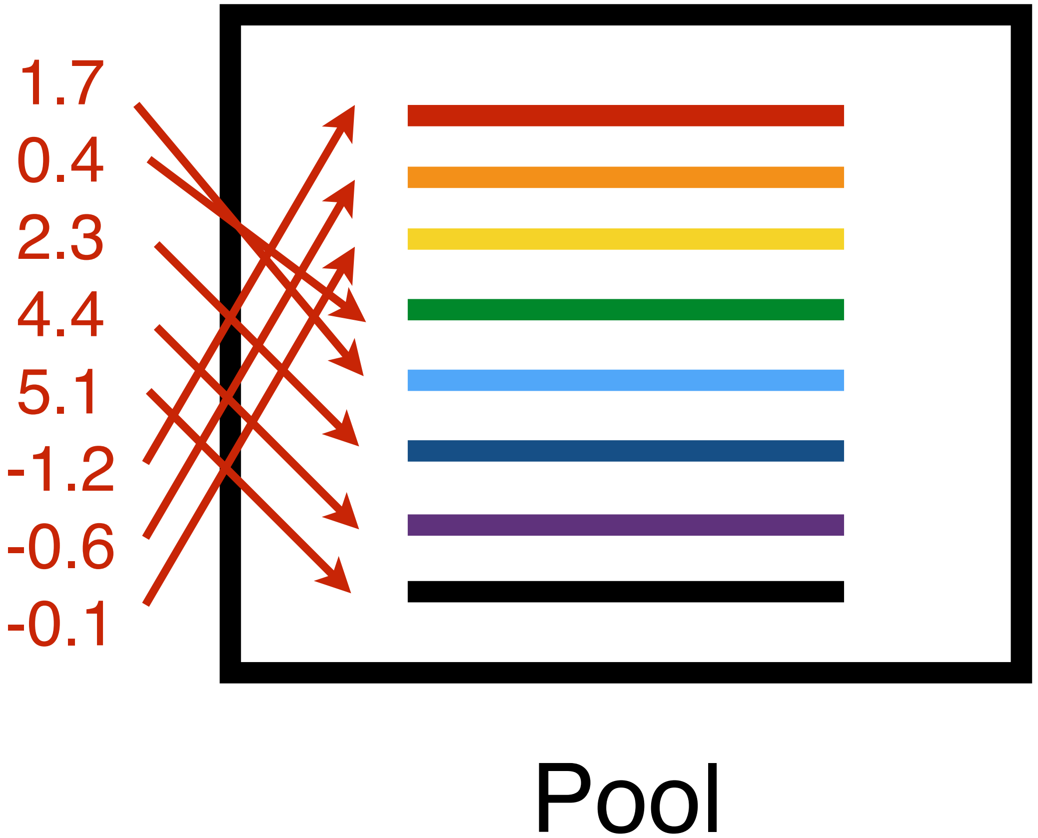

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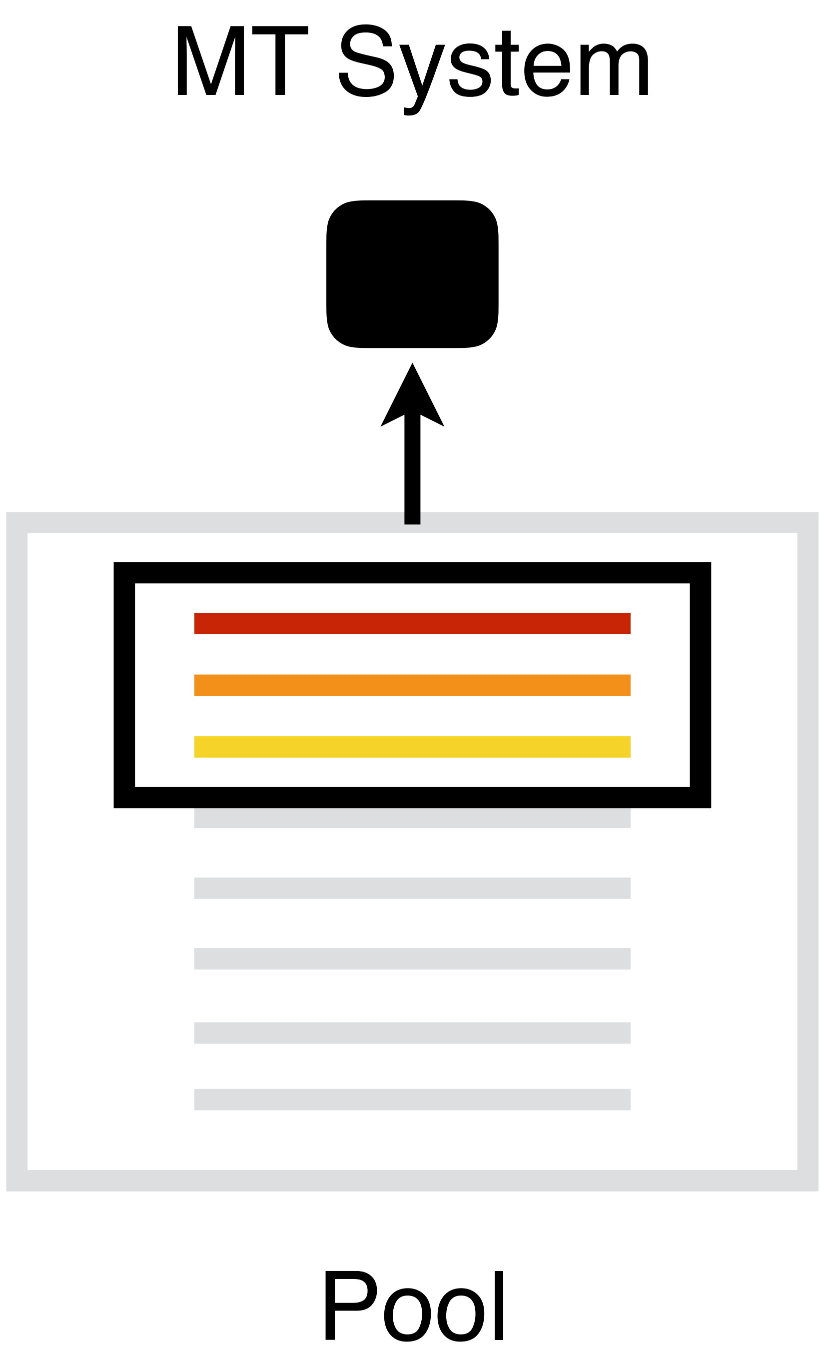


- Data selection:

  There's no data like relevant data!

Cross-Entropy Difference

$$\underset{s \in Pool}{\operatorname{argmin}} \; H_{LM_{Task}}(s) - H_{LM_{Pool}}(s)$$

- (Sometimes called "Moore-Lewis method")
- This prefers sentences that both:
  - Are <u>like</u> the target task
  - Are <u>unlike</u> the pool average.

Class-Based Moore-Lewis

We only want the relationship between two texts.

We don't need to model either of them separately.

Deriving Intuition

From definition of cross-entropy difference:

$$\begin{aligned}
\text{score}(s) &= H_{LM_{Task}} - H_{LM_{Pool}} \\
&= -\frac{1}{N}\sum_{w \in s} \log LM_{Task}(w) - -\frac{1}{N}\sum_{w \in s} \log LM_{Pool}(w) \\
&= -\frac{1}{N}\sum_{w \in s} [\log LM_{Task}(w) - \log LM_{Pool}(w)] \\
&\propto \sum_{w \in s} \log \frac{LM_{Task}(w)}{LM_{Pool}(w)}
\end{aligned}$$

$$\boxed{\text{score}(s) \propto \sum_{w \in s} \log \frac{P_{Task}(w)}{P_{Pool}(w)}}$$

unigram frequency ratio

Not All Words Are Equal

- Scores depend on word probability ratio.
  - <u>Rare</u> word statistics aren't trustworthy
    (count close to 0)
  - <u>Fair</u> words don't affect the score
    (ratio close to 1)
  - <u>Biased</u> words matter the most
    (ratio close to 0 or very large)
- Move bias information into the corpus!

Aggregating Statistics

- Bias info alone does not change word statistics
- Need to also take some information <u>out</u>!
- Collapse words-of-a-kind together:

  Replace words with Brown cluster labels
  (fully unsupervised, for any language)

- [previously @IWSLT 2015: POS tags]

Marking Bias Explicitly

- Replace word with its cluster label,
  and add a suffix indicating unigram frequency ratio

- “ozeanen” —> “862/+”
  Brown cluster #862,
  1 order of magnitude more common in the Task

- “…” —> “3/-“
  Brown cluster #3,
  1 order of magnitude more common in the Pool

Marking Bias Explicitly

- “ozeanen” —> “862/+”
  Brown cluster #862,
  1 order of magnitude more common in the Task

- Now each corpus knows about the other one!

- Bias (ratio) changes for each Task/Pool pair,
  allows for nuance in relationship

Cluster-based Methodology

- Drop-in addition to existing method!
  1. Compute Brown clusters for the corpora
  2. Compute vocab statistics and ratios
  3. Transform text
  4. Do cross-entropy difference data selection
  5. Put words back in, and carry on!

- Data selection:

  There's no data like relevant data!

- Language difference models:

  model each corpus <u>relative to the other one</u>

Experimental Setup

- German --> English translation

- Task: TED, 218 k lines (4 m tokens)
  Pool: WMT, 17.6 m lines (235 m tokens)

- Vocab (De): 1.1m
  Vocab (En): 900k

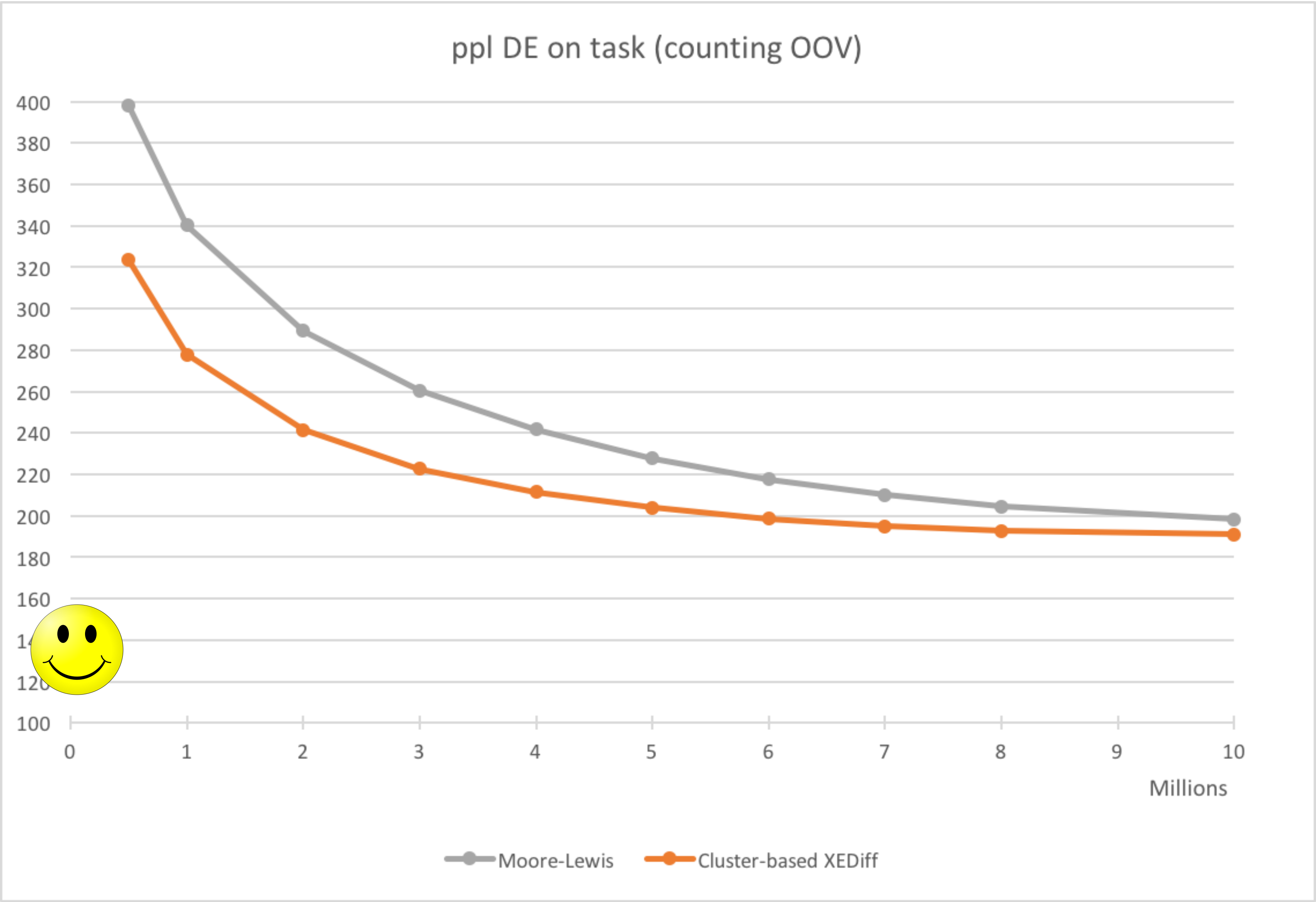
- 1,000 Brown clusters x 8 bias labels,
  collapsing lexicon to < 3000 types

In-Domain Perplexity

- cluster-based:

  -20 ppl

-

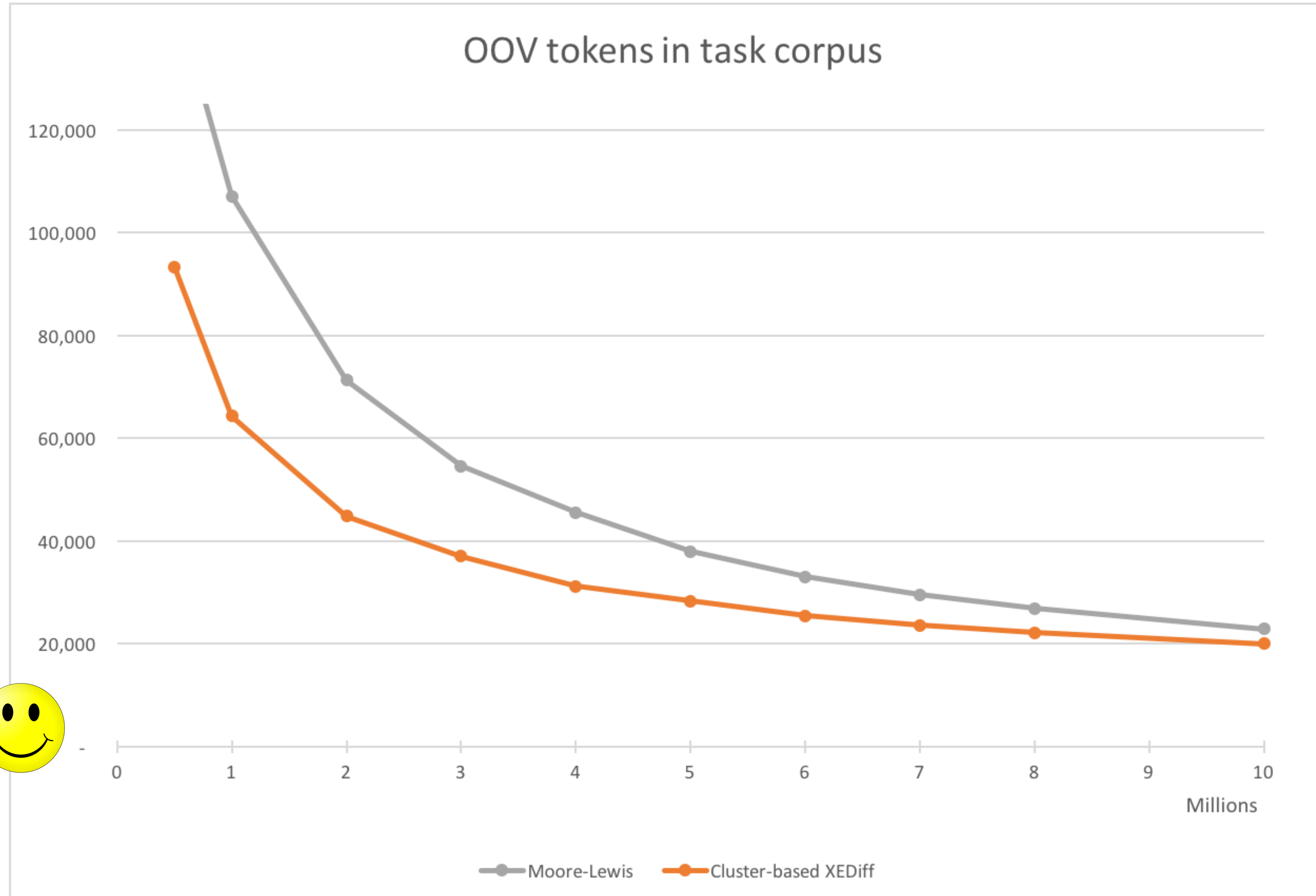


In-Domain Lexical Coverage

- cluster-based:

  -33% oov

-



Moore-Lewis Limitations

Cross-entropy difference…

… treats Task and Pool as the opposing ends of a single spectrum "IN = Good, OUT = Bad"

… Not guaranteed to model nor cover in-domain data. LM_{TASK} likes them; this is necessary, but not sufficient.

… No intuition as to how many sentences to select. Grid search doesn't count.

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BUT IT WORKS — WHY CHANGE?

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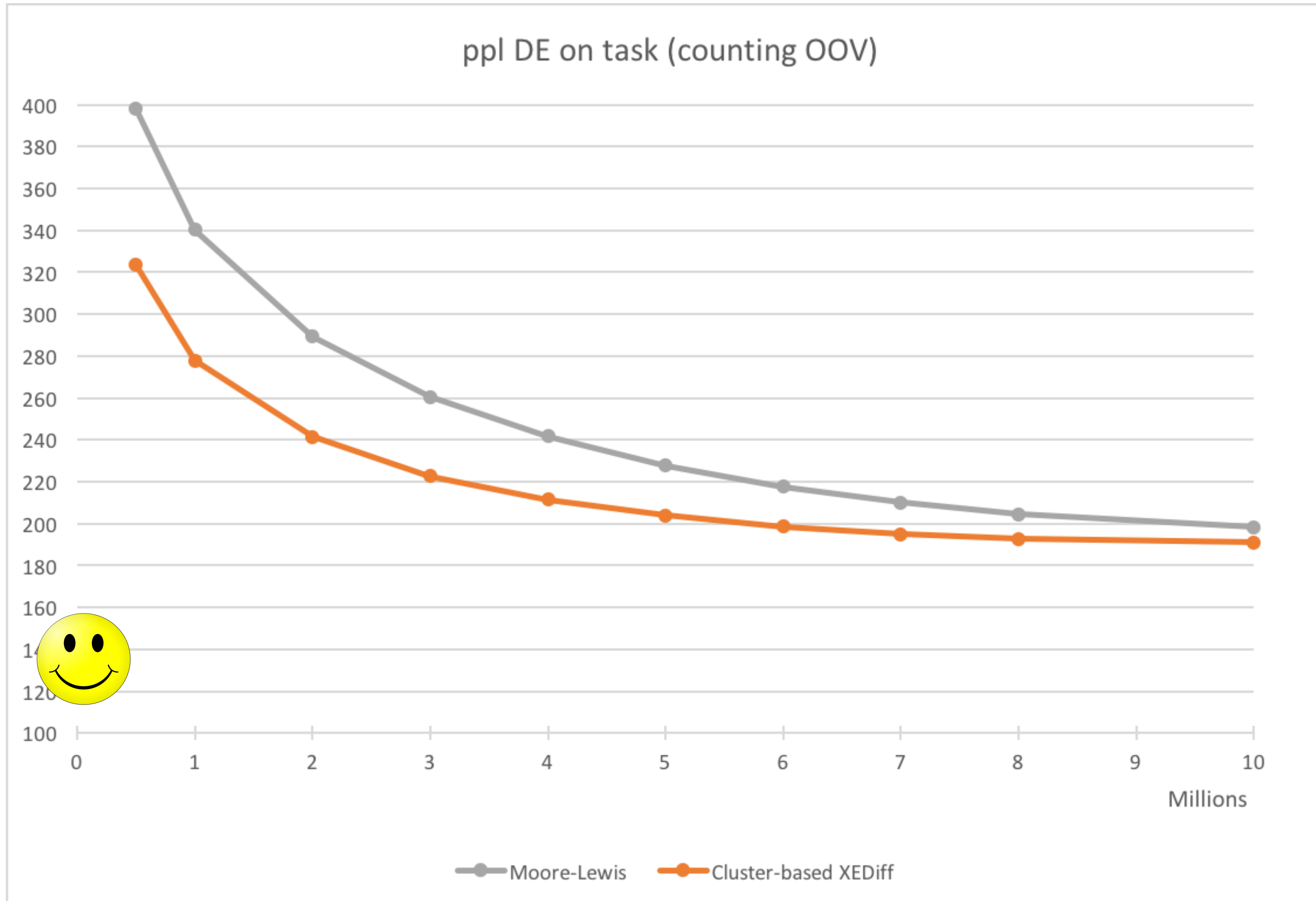

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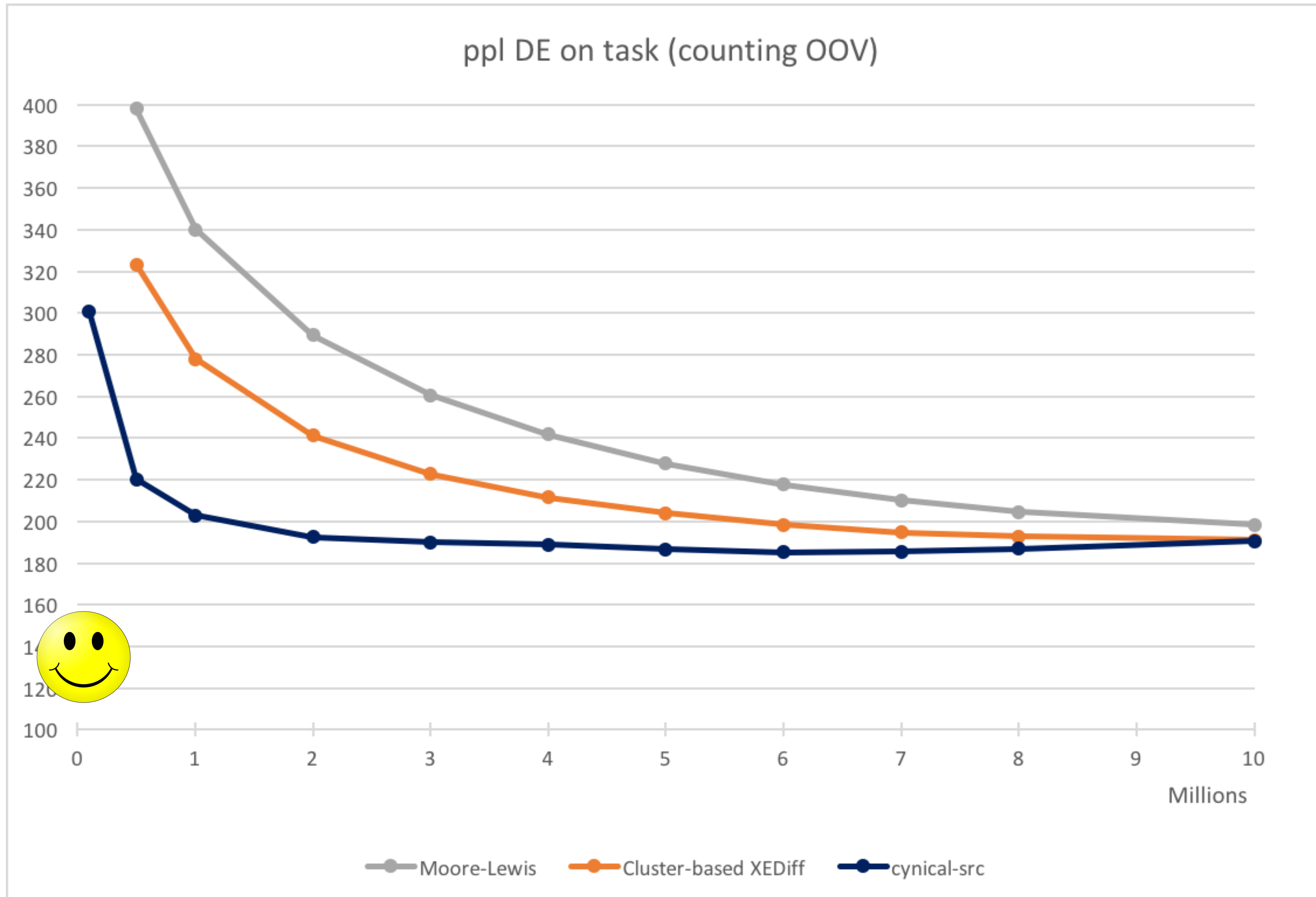

- cynical:

  -30 ppl

…and -66% less data.

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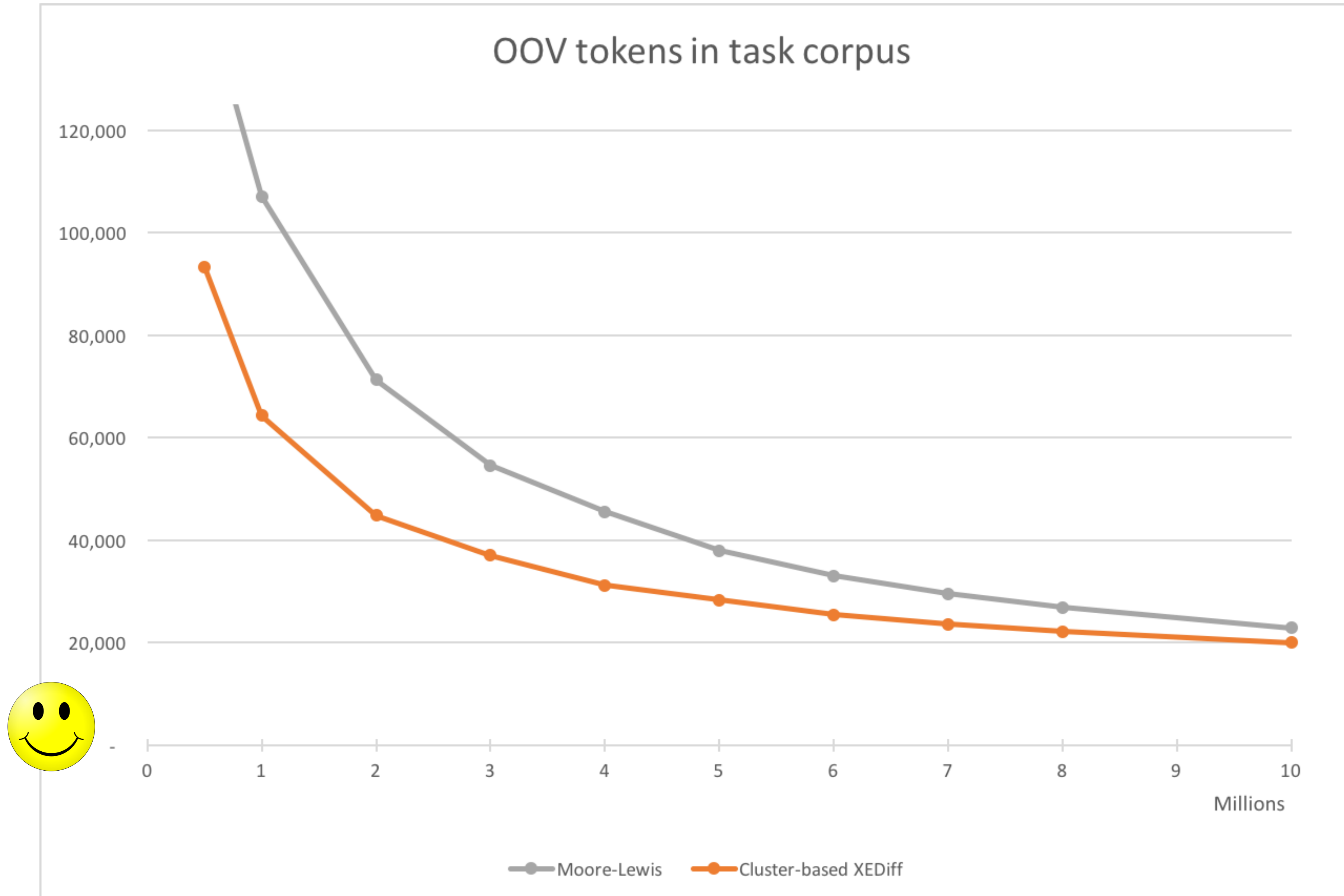

In-Domain Lexical Coverage

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- cynical:

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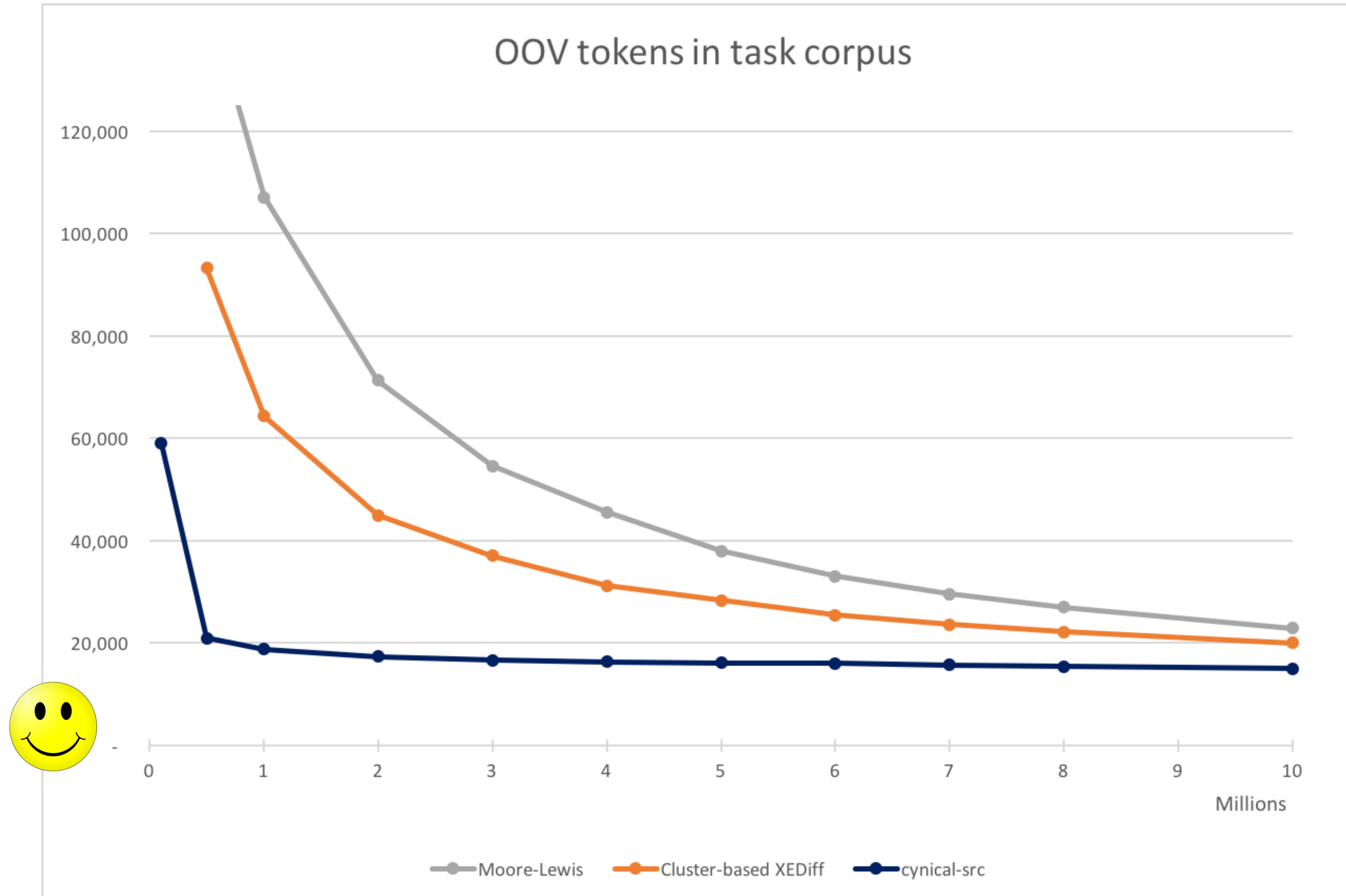

Cynical Motivation

Cross-entropy difference…

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BUT IT WORKS — WHY CHANGE? …AH.

Cynical Data Selection

- “an incremental greedy selection scheme based on relative entropy, which selects a sentence if adding it to the already selected set of sentences reduces the relative entropy with respect to the in-domain data distribution” [Sethy et al, 2006]

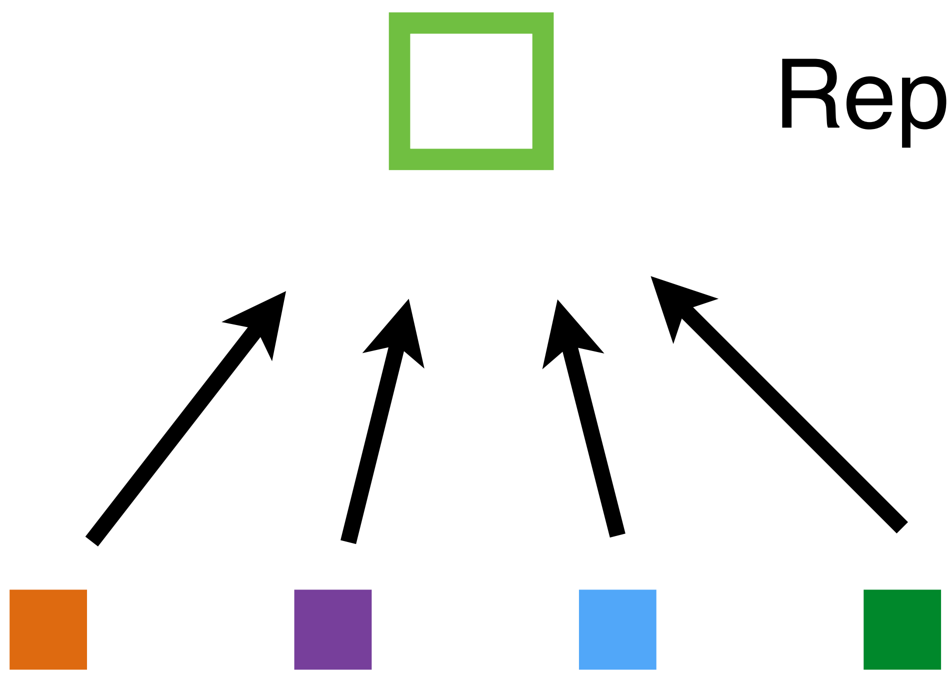
- incrementally grow the training corpus only based on how **useful** the data is

- “does it help me **now**?”

Cynical Data Selection

- How many bits of information would we learn
  if we added this line to our corpus?
- Only add sentences that can be **proven** to make the model better.
- Pick most informative lines first.

Cynical Selection Process

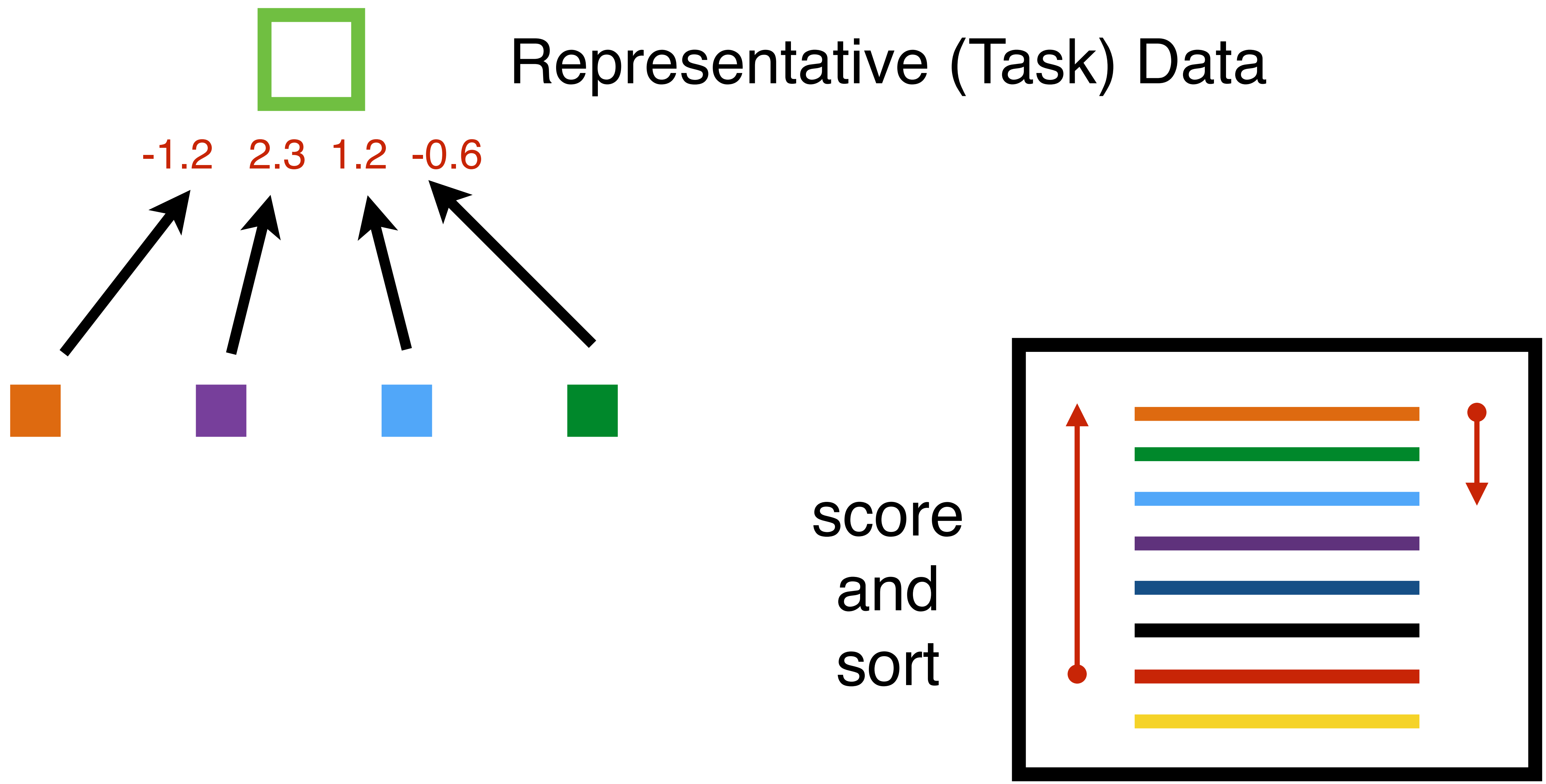


Representative (Task) Data

Can it model?

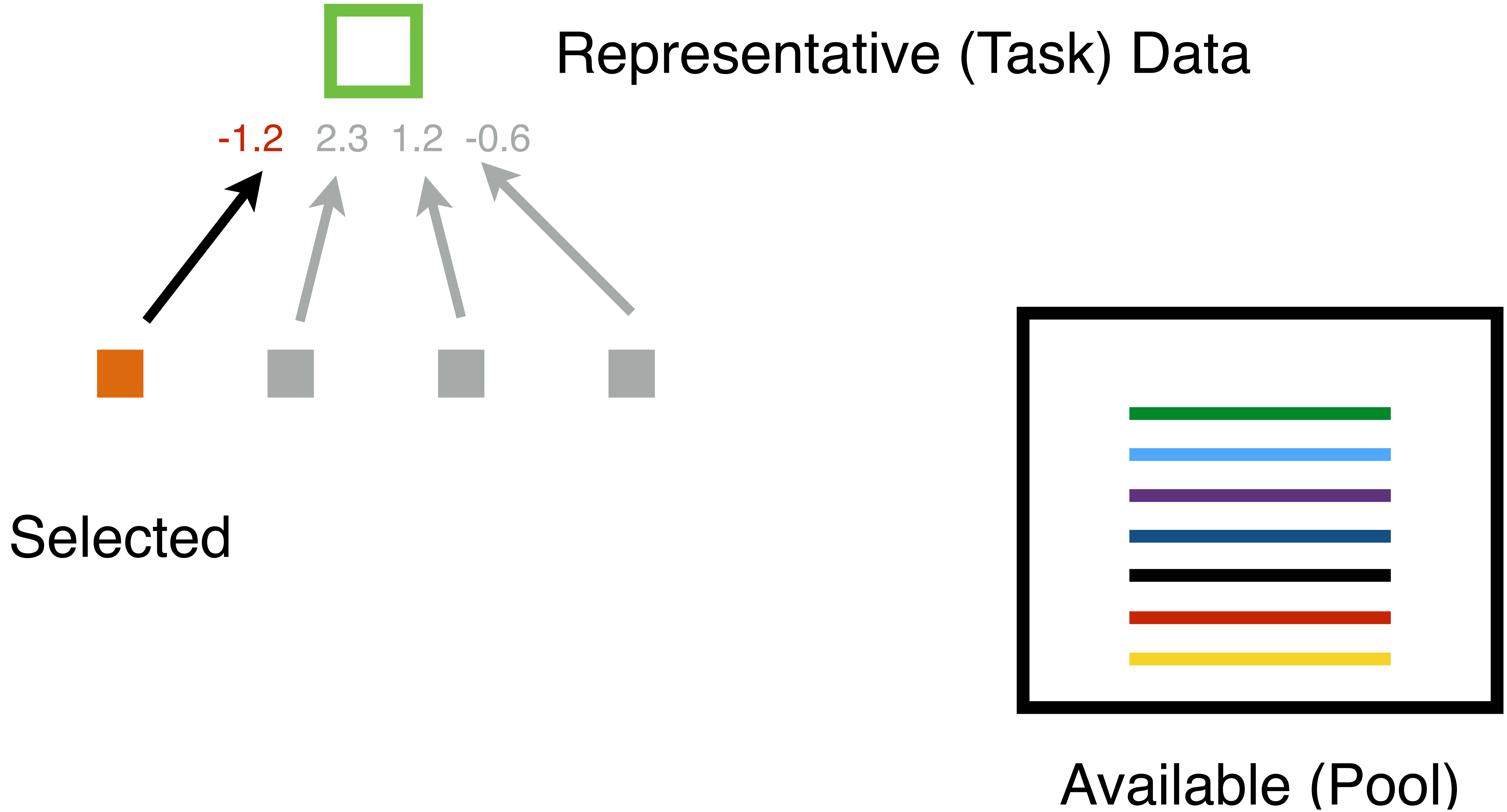
Available (Pool)

Cynical Selection Process



Available (Pool)

Cynical Selection Process



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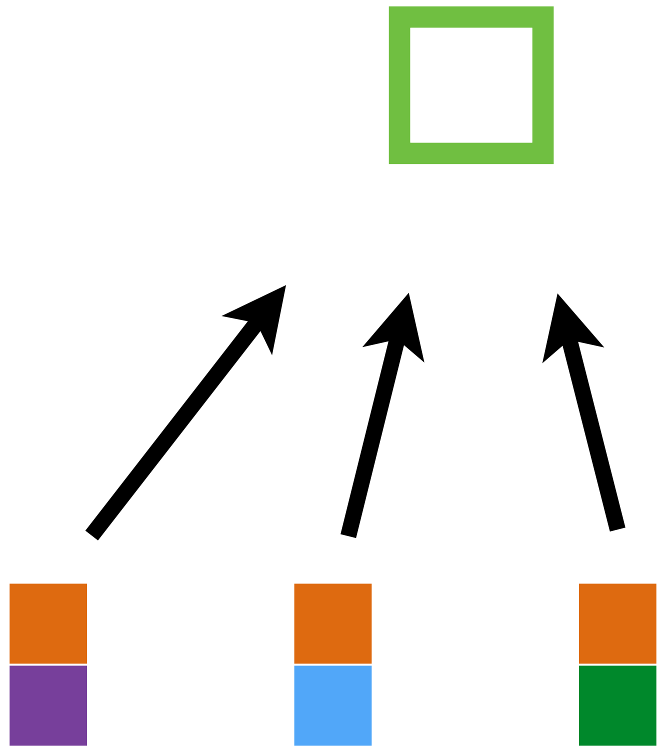

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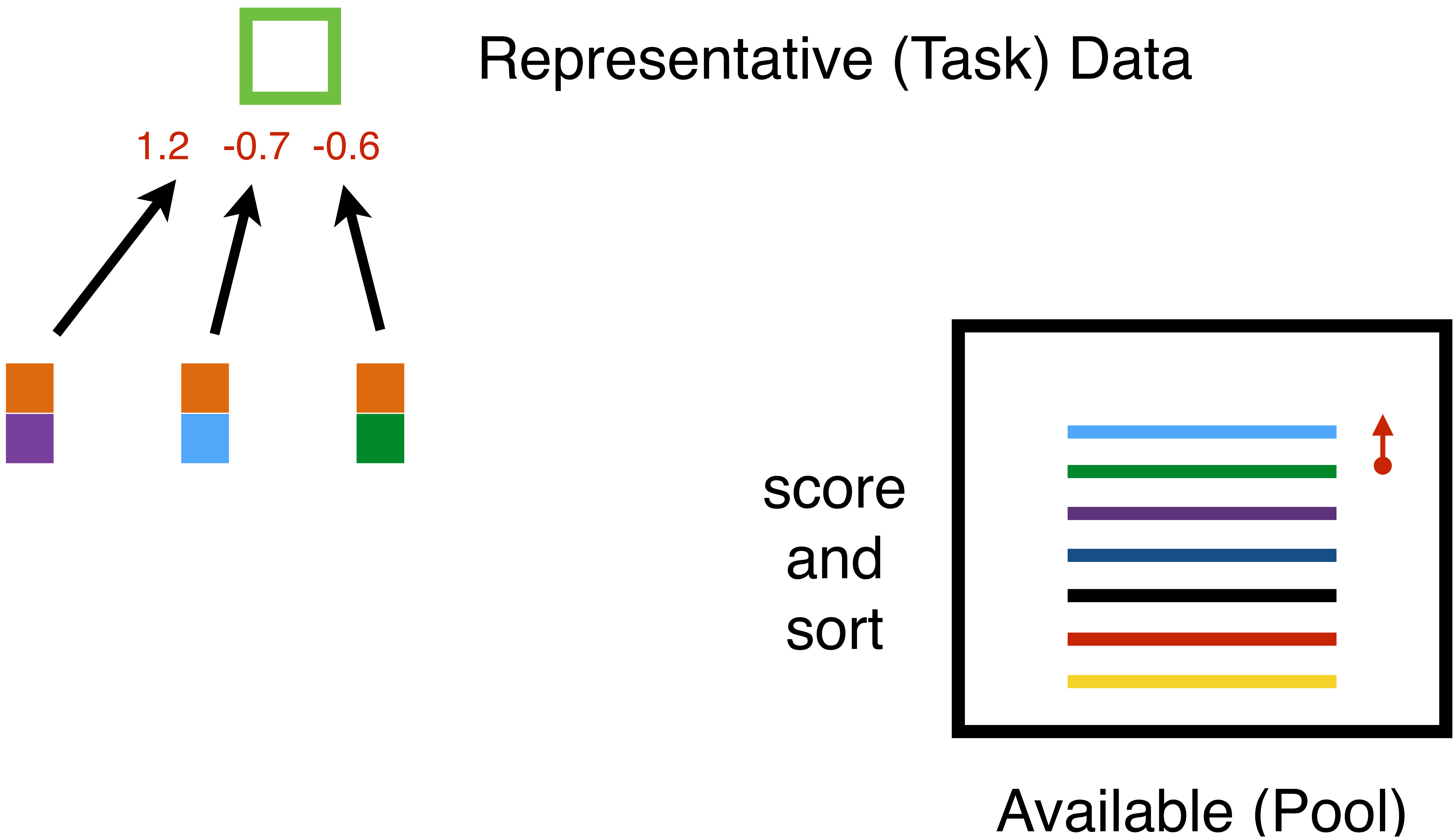

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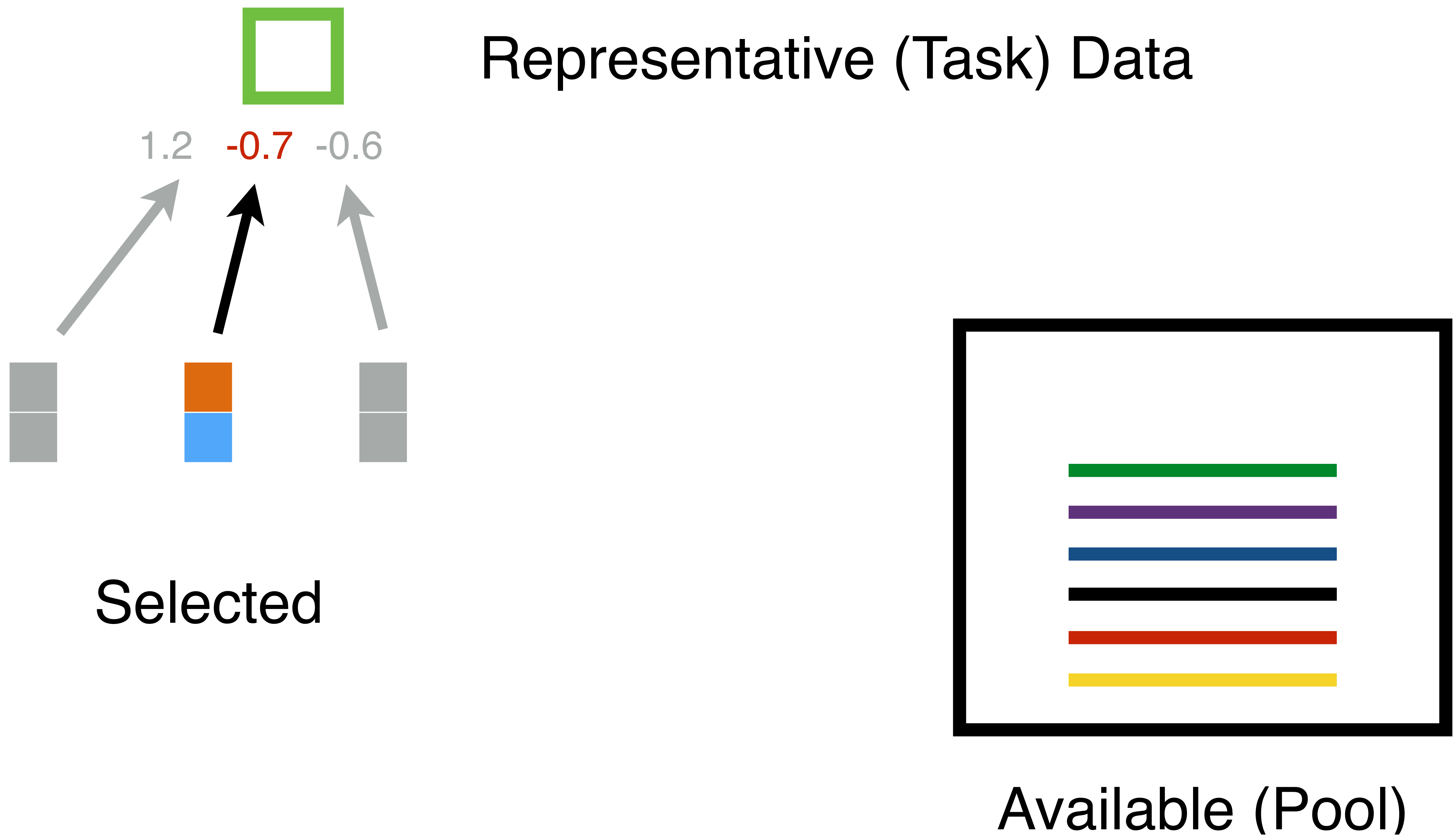

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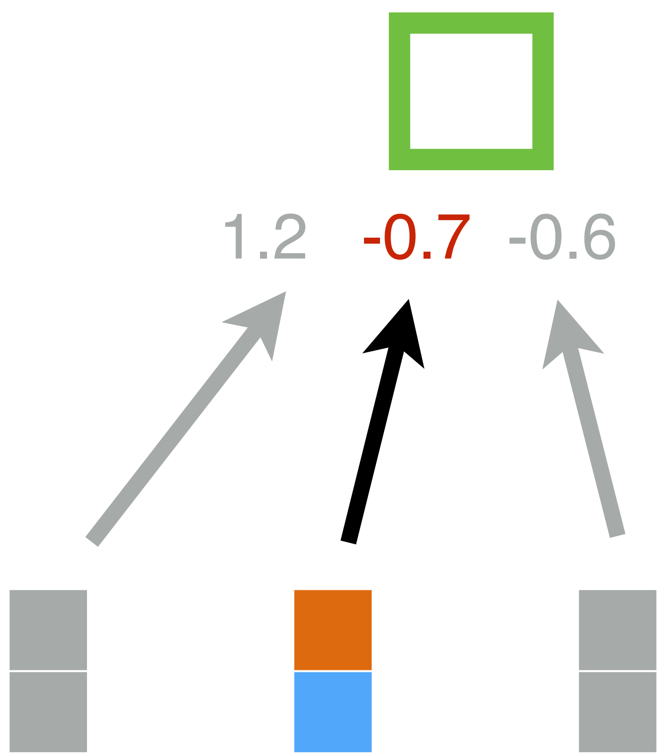


Representative (Task) Data

Where does this number come from?

What does it mean?

Available (Pool)

Quantifying Subset Score

- Pick any *n* lines. Is that subset any good?
- See how well they model the task !
- Cross-entropy between subset and the task is:

$$H_n(\mathrm{REPR}) = -\sum_{v \in V_{\mathrm{REPR}}} \boxed{\frac{C_{\mathrm{REPR}}(v)}{W_{\mathrm{REPR}}} \log \frac{C_n(v)}{W_n}}$$

(bits of entropy)

P(n) log Q(n)

Inductive Step

- After picking *n* lines, how do we pick line *n+1* ?
- Need to score all potential choices.
- We already computed H_n , so

$$H_{n+1} = H_n + \underset{n \to n+1}{\Delta H}$$

Decompose as:

$$H_{n+1} = H_n + \underset{n \to n+1}{\text{Penalty}} + \underset{n \to n+1}{\text{Gain}}$$

Greedy Cross-Entropy Delta

[Sethy/Georgiou/Narayanan 2006]

$$\underset{n\rightarrow n+1}{\Delta H} = H_{n+1} - H_n$$

$$= \left(- \sum_{v \in V_{\text{REPR}}} \frac{C_{\text{REPR}}(v)}{W_{\text{REPR}}} \log \frac{C_{n+1}(v)}{W_{n+1}} \right) - \left(- \sum_{v \in V_{\text{REPR}}} \frac{C_{\text{REPR}}(v)}{W_{\text{REPR}}} \log \frac{C_n(v)}{W_n} \right)$$

$$\underset{n\rightarrow n+1}{\Delta H} = \boxed{\underbrace{\log \frac{W_n + w_{n+1}}{W_n}}_{Penalty}} + \boxed{\underbrace{\sum_{v \in V_{\text{REPR}}} \frac{C_{\text{REPR}}(v)}{W_{\text{REPR}}} \log \frac{C_n(v)}{C_n(v) + c_{n+1}(v)}}_{Gain}}$$

Penalty Term

$$\underbrace{\log \frac{W_n + w_{n+1}}{W_n}}_{Penalty}$$

All words in line

- Each word we add increases the penalty for the line
- Bias towards shorter sentences
- Penalty for line decreases over time

Gain Term

Only relevant words

$$\underbrace{\sum_{v \in V_{\text{REPR}}} \frac{C_{\text{REPR}}(v)}{W_{\text{REPR}}} \log \frac{C_n(v)}{C_n(v) + c_{n+1}(v)}}_{Gain}$$

- Rewards each word in line that is also in the task
- Bigger reward for higher-probability words
- Bias towards longer sentences
- Gain of line also decreases over time

Selection Criterion

$$\underset{n \to n+1}{\Delta H} = \underset{n \to n+1}{\text{Penalty}} + \underset{n \to n+1}{\text{Gain}}$$

- Computable separately
- Cheap to update
- Approximations are upper bounds:
  - Easy to sort
  - High precision (no bad lines with good scores)

Selection Criterion

$$\underset{n \to n+1}{\Delta H} = \underset{n \to n+1}{\text{Penalty}} + \underset{n \to n+1}{\text{Gain}}$$

- Delta H < 0
  This line adds information (lowers entropy). Select it!

- Delta H > 0
  This sentence makes your model dumber. Leave it!

- Delta H starts < 0, and increases over time.
  Score passes zero when it runs out of useful sentences. Ok to stop!

Naïve Algorithm

- Picking n+1:
  - Compute the Delta H score for each sentence remaining in AVAIL.
  - Sort the sentences in AVAIL by Delta H
  - Select sentence with the best (lowest) score.
  - Remove it from AVAIL.
- Loop

Why Not Do It Like That?

- (*i.e.* "Why wasn't this done in 2006?")
- N iterations $O(N)$
  - Each updating W_{AVAIL} words $O(N)$
    and sort N lines to find best $+ O(N \log N)$
- Total: $= O(N^2 + N^2 \log N) > O(N^2)$
- No thanks!

Implementation

- naïve iterative greedy selection: at least $O(N^2)$
- "Perfect is the enemy of Good"
- What if we just want 'good' and not 'best' ?
- Doable in $O(N \log N)$

Not All Words Are Equal

- Sentence gain score decomposes into word scores:

$$\underset{n \to n+1}{\text{Gain}} = \sum_{v \in v_{n+1}} \underset{n \to n+1}{\text{Gain}}(v)$$

- Dominated by one or two of the word (type) terms, because of Zipfian distribution

“Good Enough”

- What about word with the best gain estimate?
- It will help to <u>eventually</u> add a line with that word.
- We will pick many sentences—
  no harm in adding now.

“Good Enough”

- Pick best sentence containing
  the word with best gain.

- Might not be best sentence, but is good sentence.

- Reduces # lines to evaluate at each step.

Lowering Complexity

- N iterations — N
  - Each updating V words, sorting V words to find best — $V + V \log V$
  - Update and sort AVAIL(v') lines — $N^{1/3} + N^{1/3} \log N^{1/3}$
- Total: — $O(N\,V \log V)$

Squish Lexicon

- Cynical Selection complexity depends on size of V
- Reduce lexicon with insight from Class-based Moore-Lewis
- Focus on words biased towards TASK and away from AVAIL
- Collapse all other words into 5 classes
- Final vocabulary: ~30k words.

“Tractable Enough”

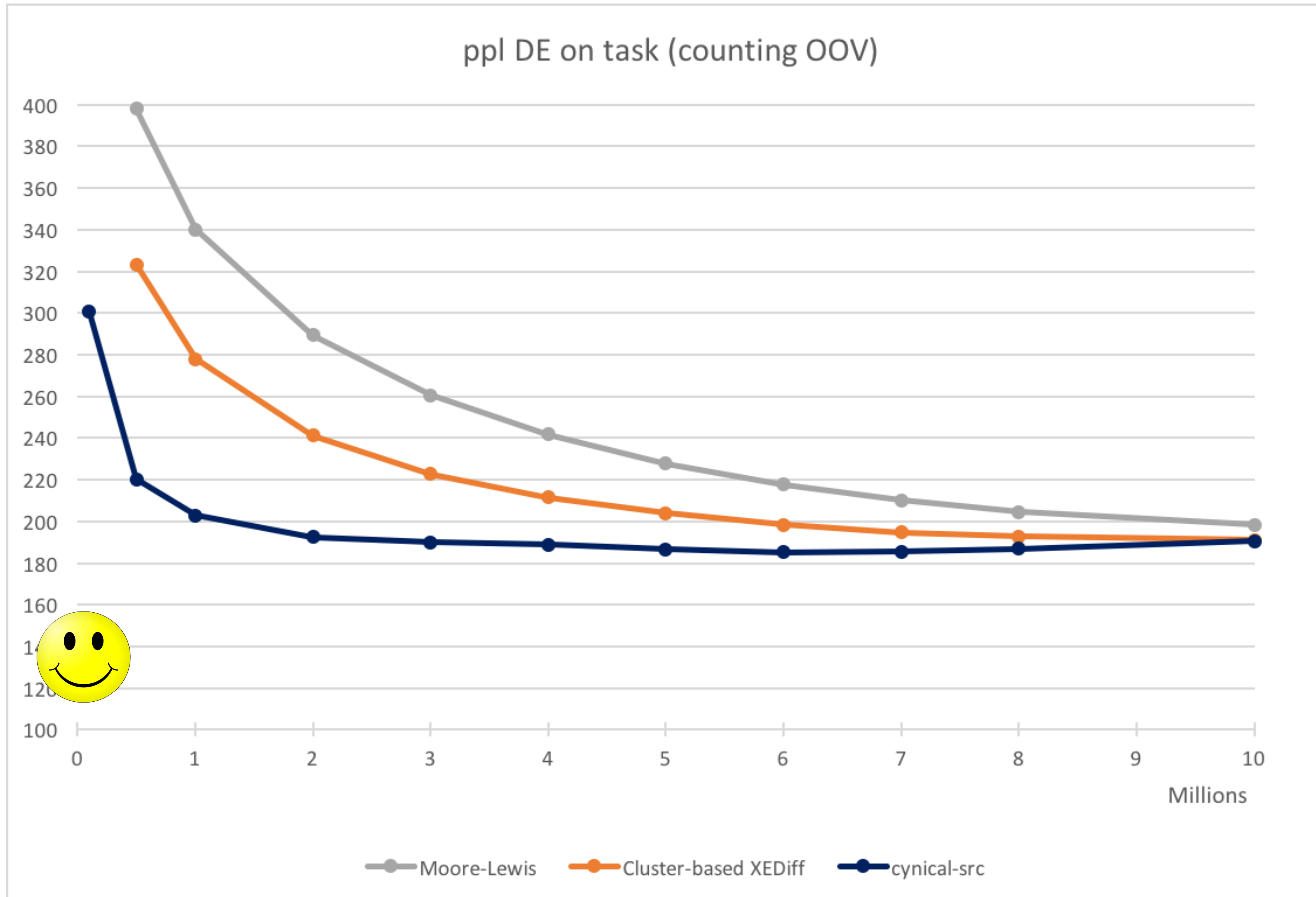
- Complexity of O(N log N) achievable with reduced lexicon and dynamically-sized batching.
- Still super-linear!
  But not terribly (experiments ran in 0.5 - 1 day)
- Also, do not need to run to completion —
  stop when estimated entropy gain stays above 0.

Algorithm in Practice

- Picking n+1:
  - Compute Word Gain Estimate (WGE) for all V
  - Sort, then select word v’ with best WGE
  - Compute the Delta H score for each sentence in AVAIL(v’)
    (set of sentences remaining in AVAIL that contain v’)
  - Sort AVAIL(v’) by Delta H
  - Select sentence with the best (lowest) score.
  - Remove it from AVAIL.
- Loop until best Delta H > 0 for all words.

In-Domain Perplexity

- cluster-based:
  -20 ppl



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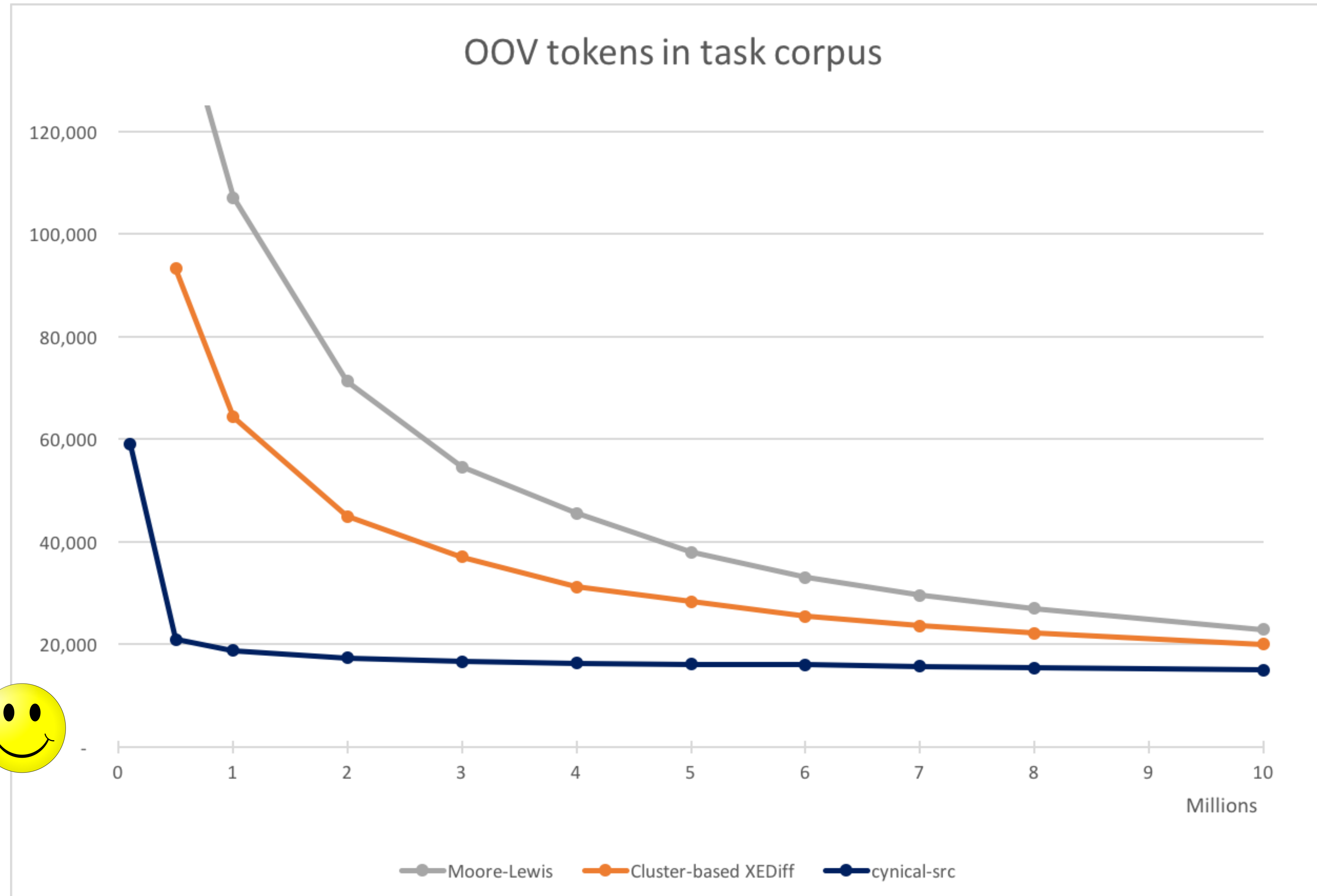

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Summary

- Data selection:

  There's no data like useful data!

- If you use Moore-Lewis, upgrade to class-based.

  Always better, runs on tiny computers.

- Cynical gives same MT results,

  with much smaller systems

  and near-perfect coverage.

  Always better, runs on big computers.

Thanks!

Lucía Santamaría : lucsan@amazon.com

Cynical Selection available:

https://github.com/amittai/cynical

(totally open-source, MIT license, Amazon is not responsible for my bugs)

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