Discriminative Training part 2

Machine Translation
Lecture 12

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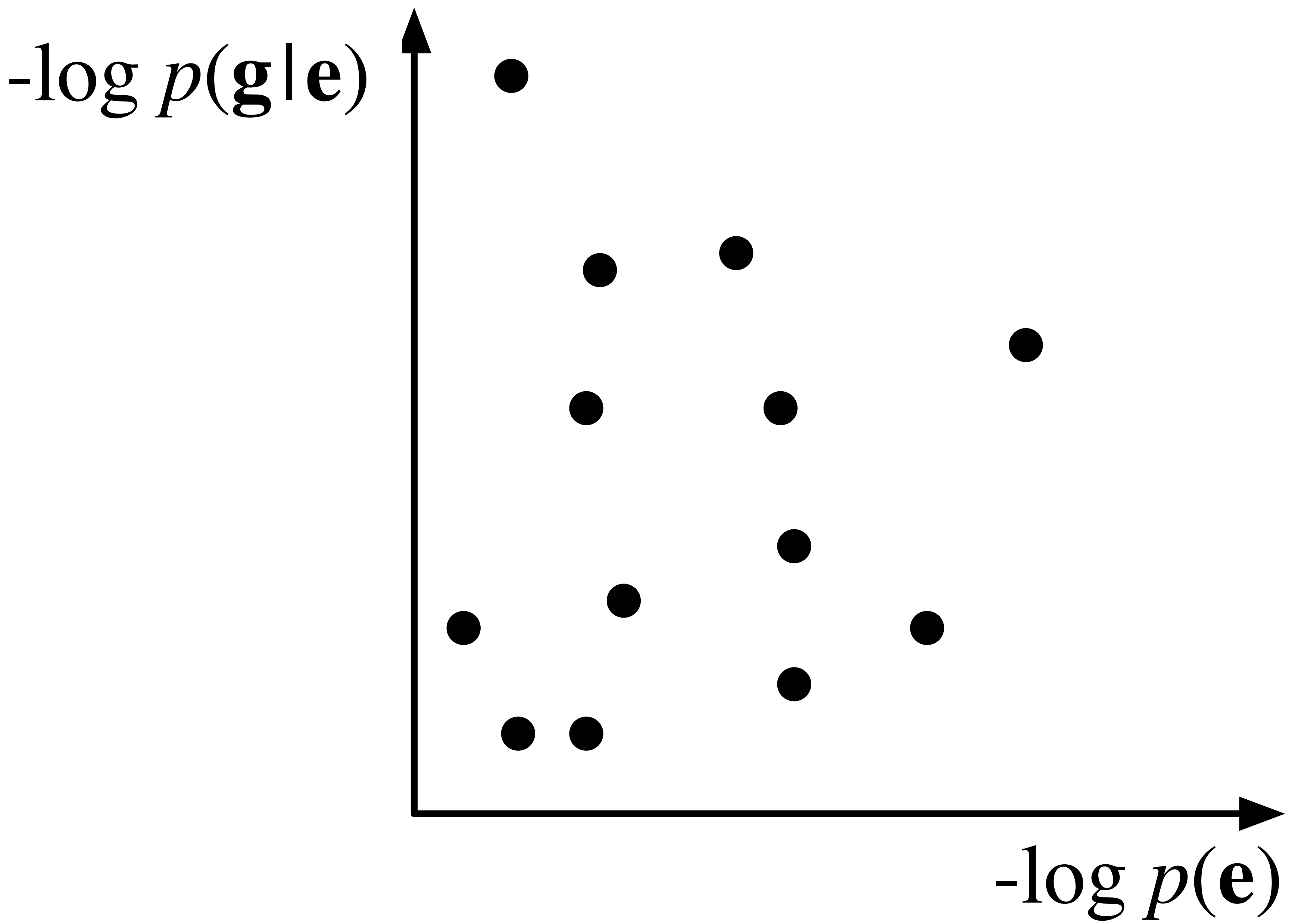
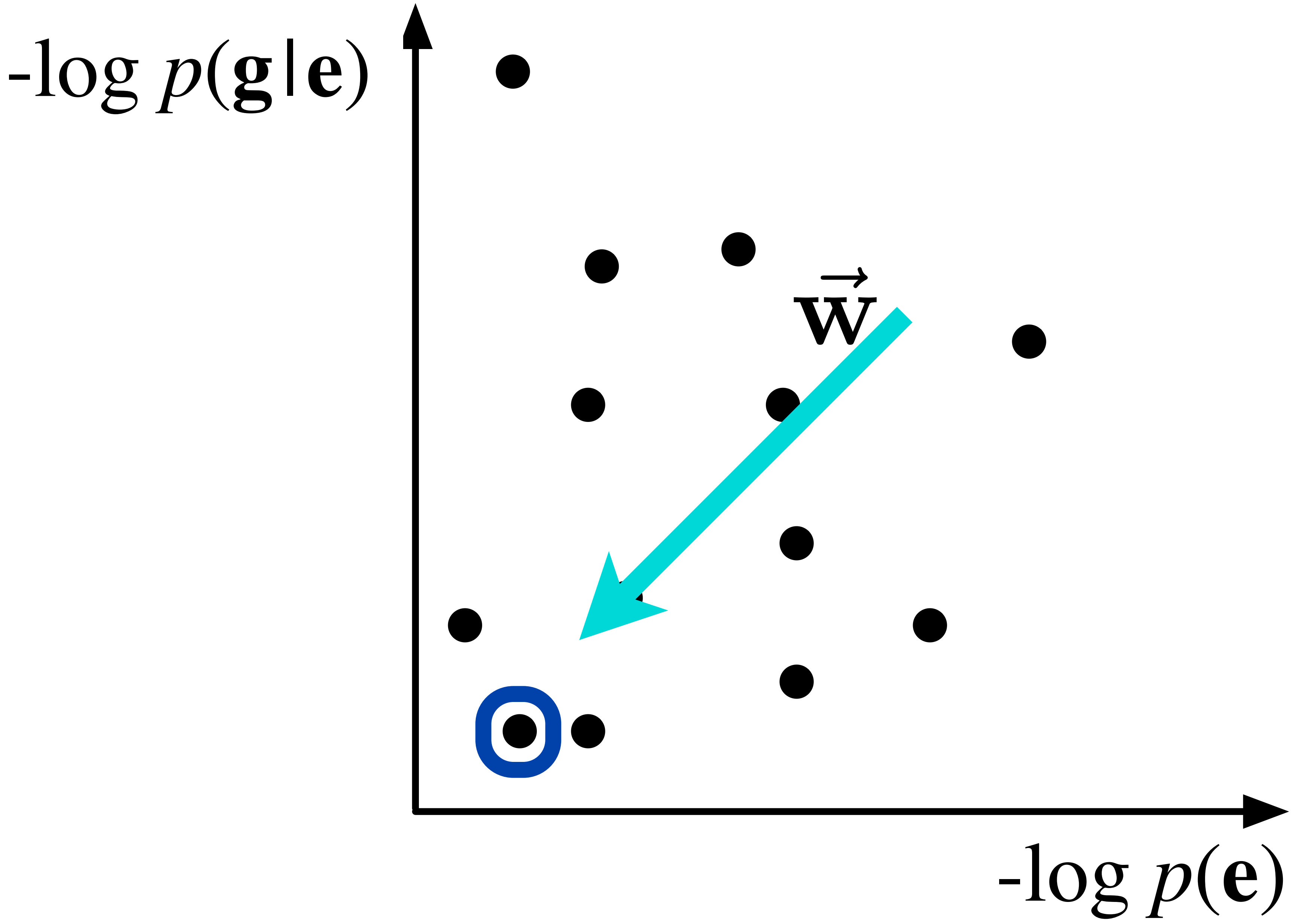
TAs: Mitchell Stern, Justin Chiu

Website: mt-class.org/penn

The Noisy Channel



As a Linear Model



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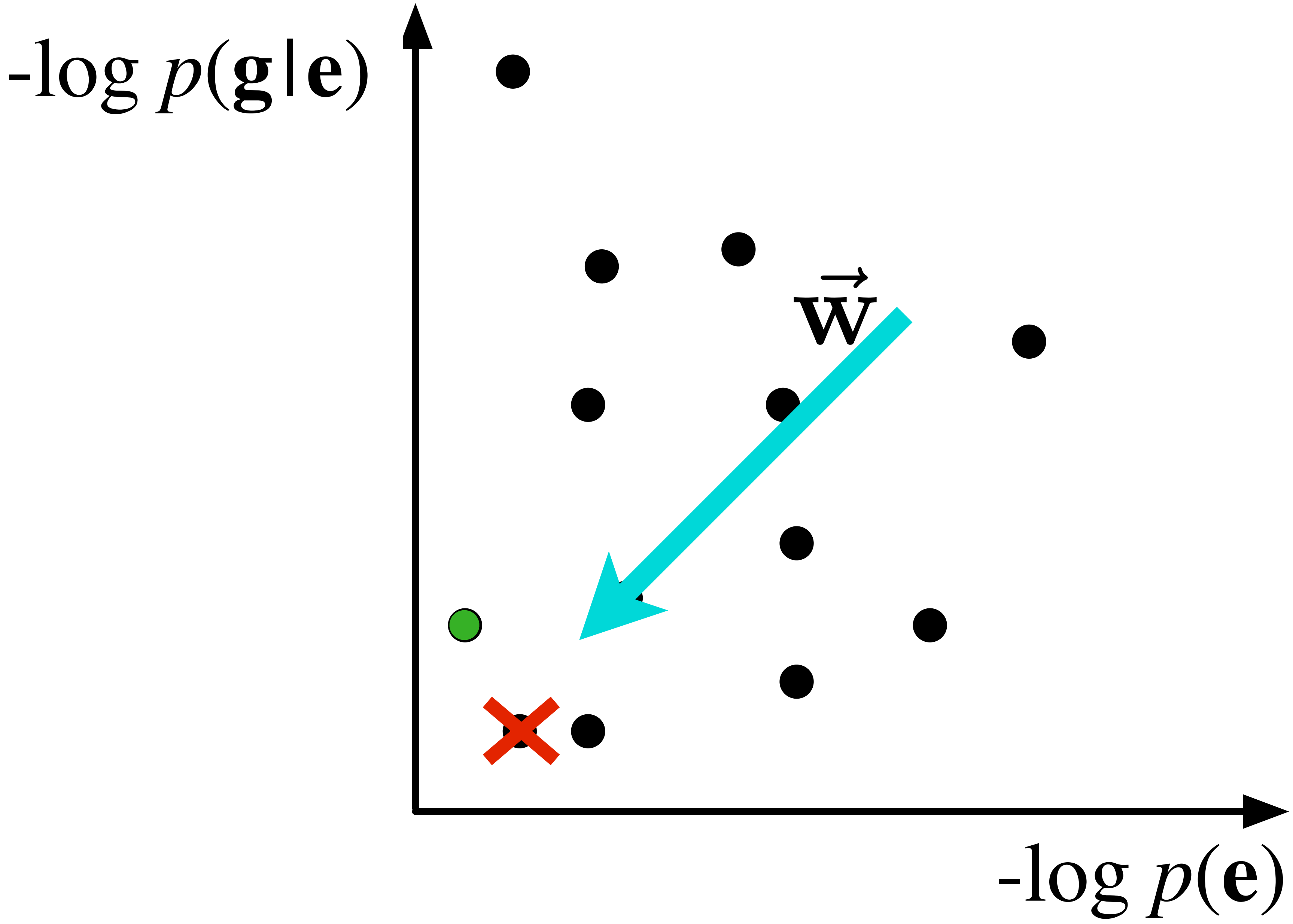

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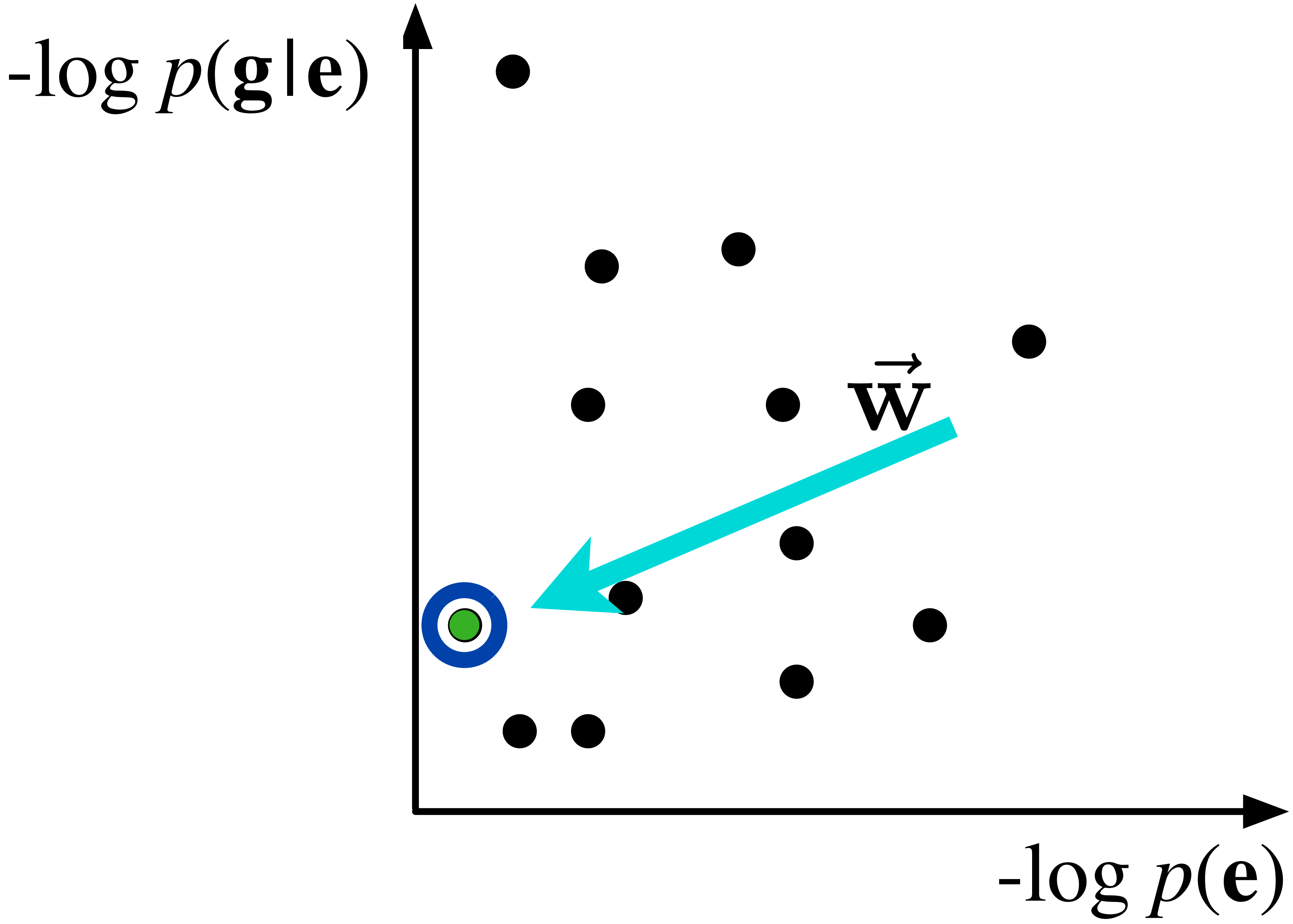

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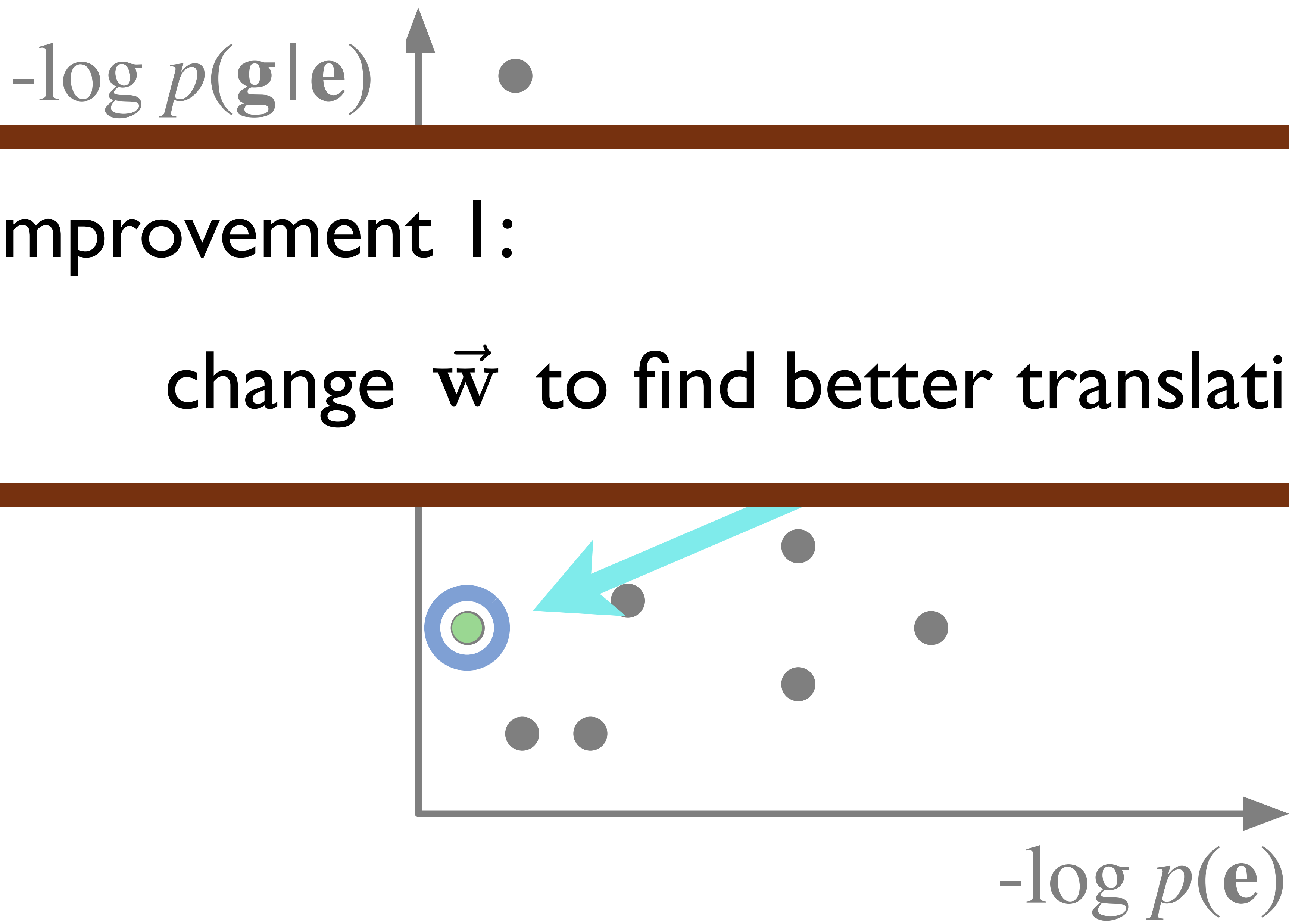
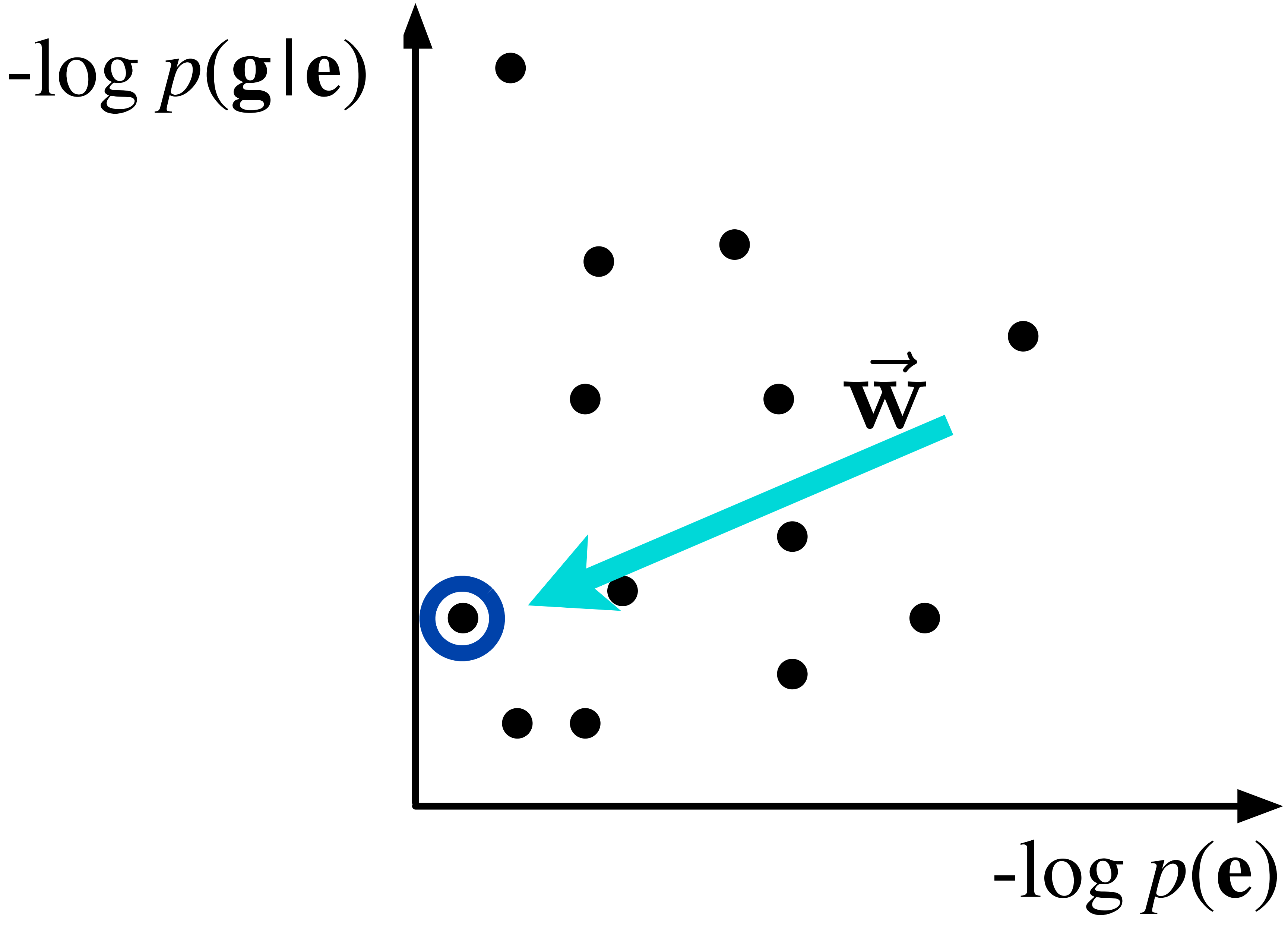


Improvement 1:

change $\vec{\mathrm{w}}$ to find better translations

As a Linear Model



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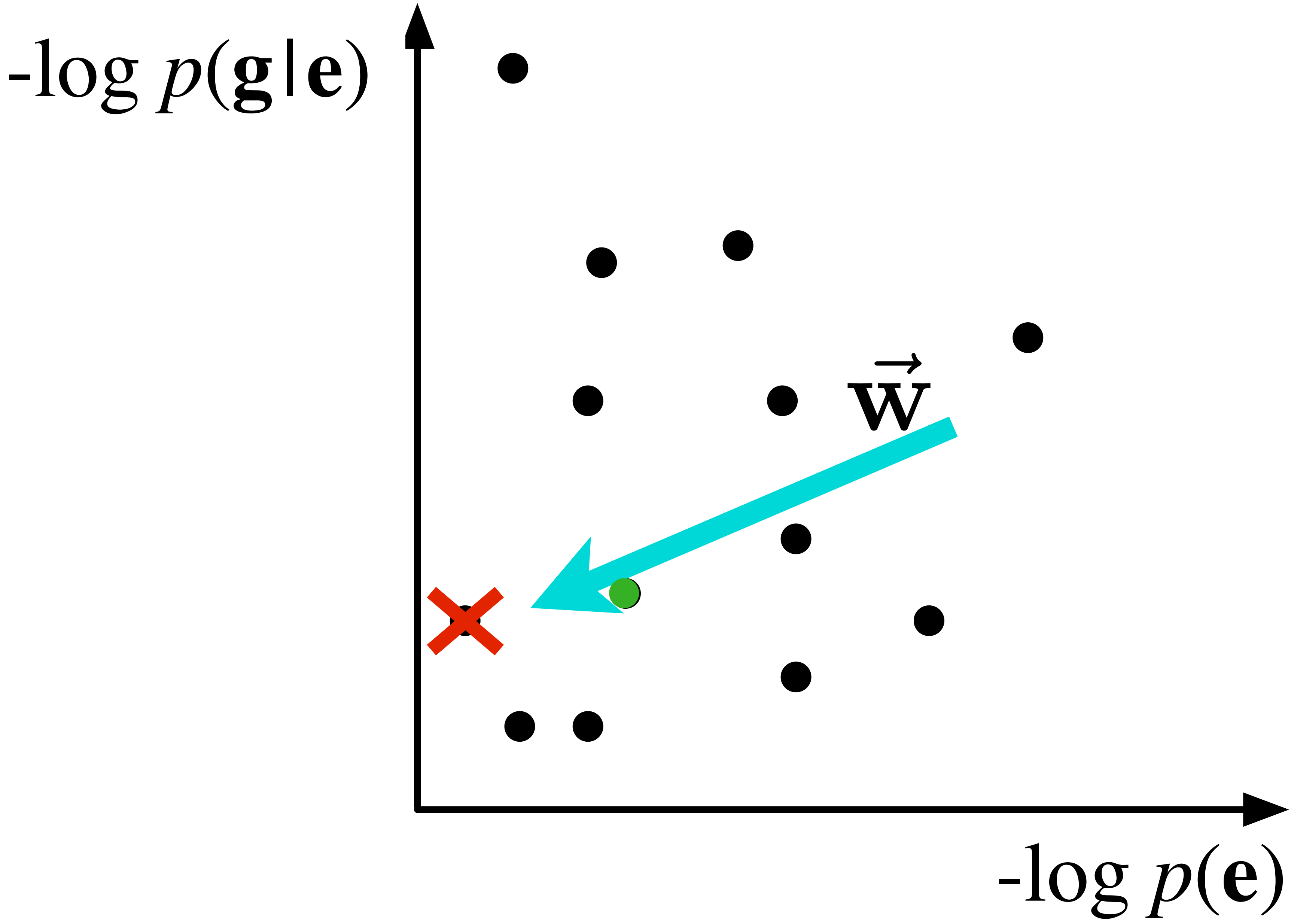

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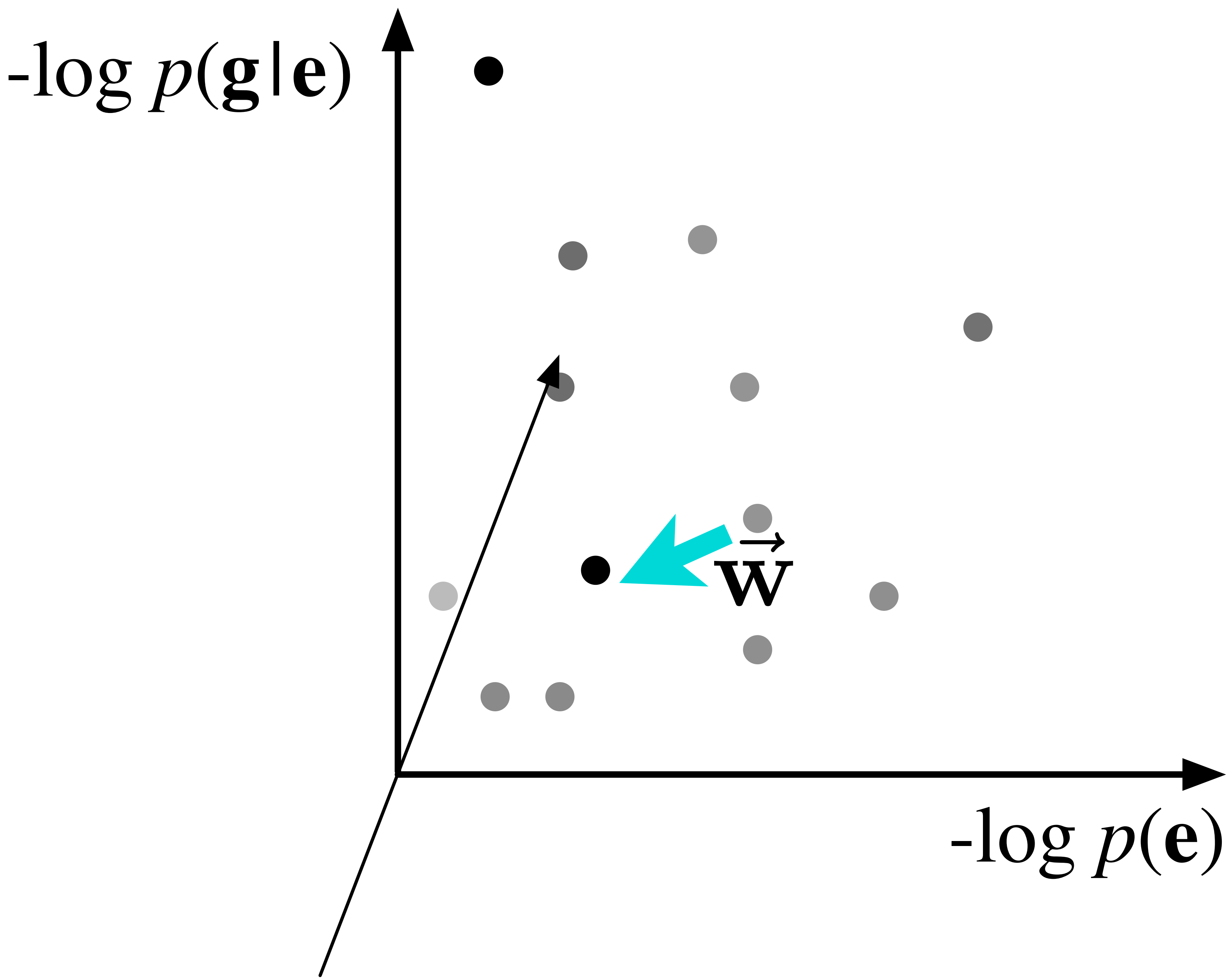

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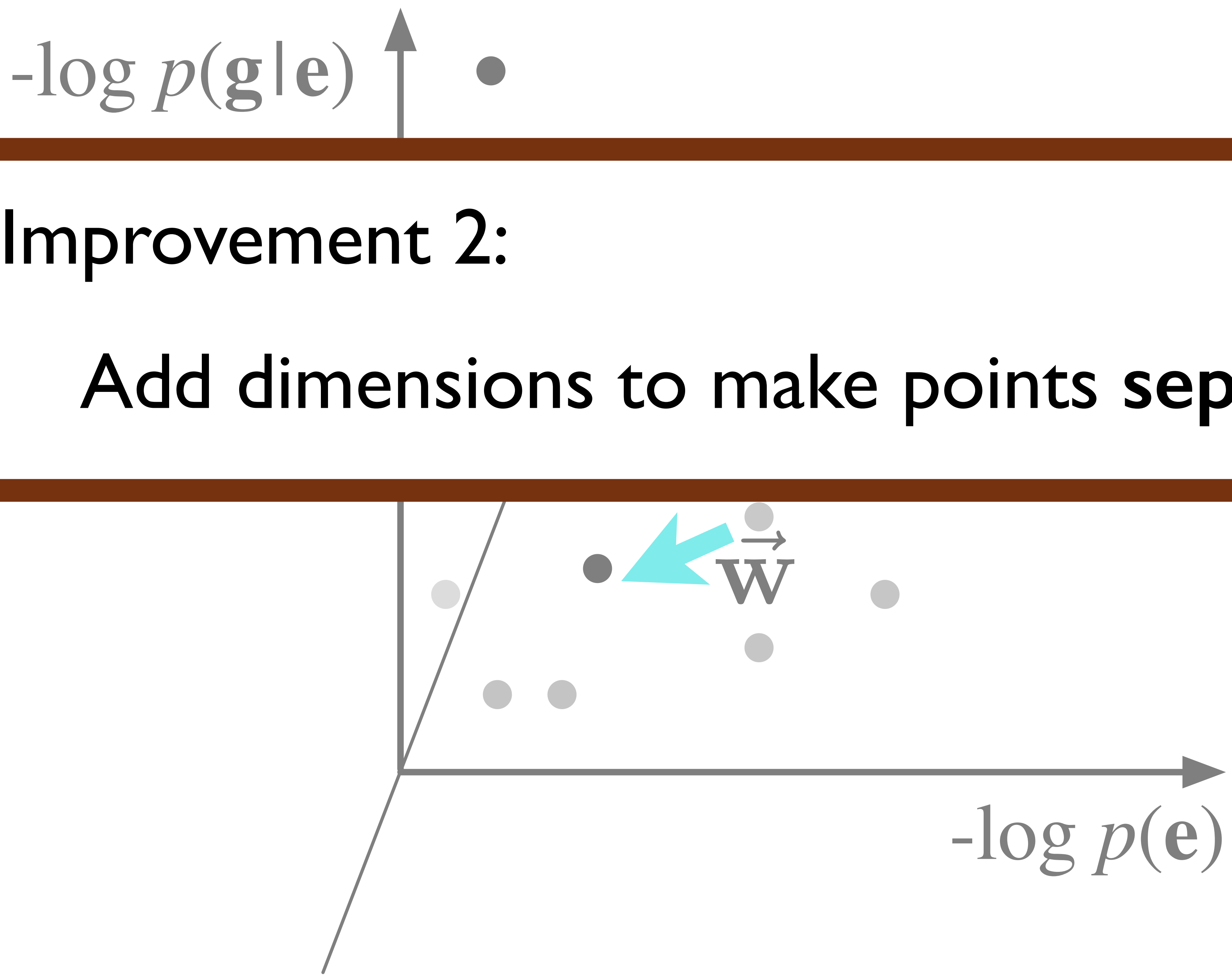


Improvement 2:

Add dimensions to make points **separable**

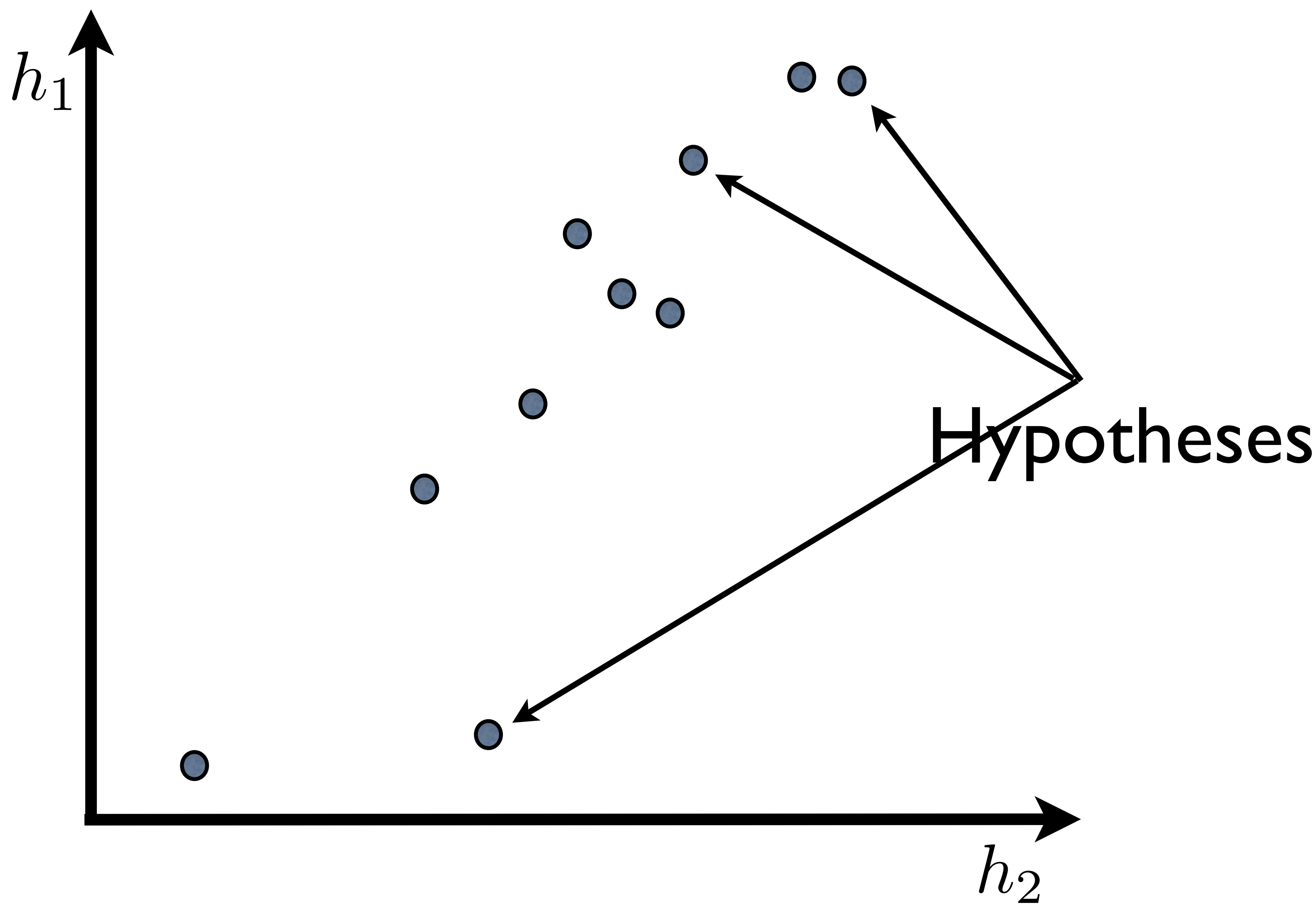
Linear Models

$$\mathbf{e}^* = \arg\max_{\mathbf{e}} \mathbf{w}^\top \mathbf{h}(\mathbf{g}, \mathbf{e})$$

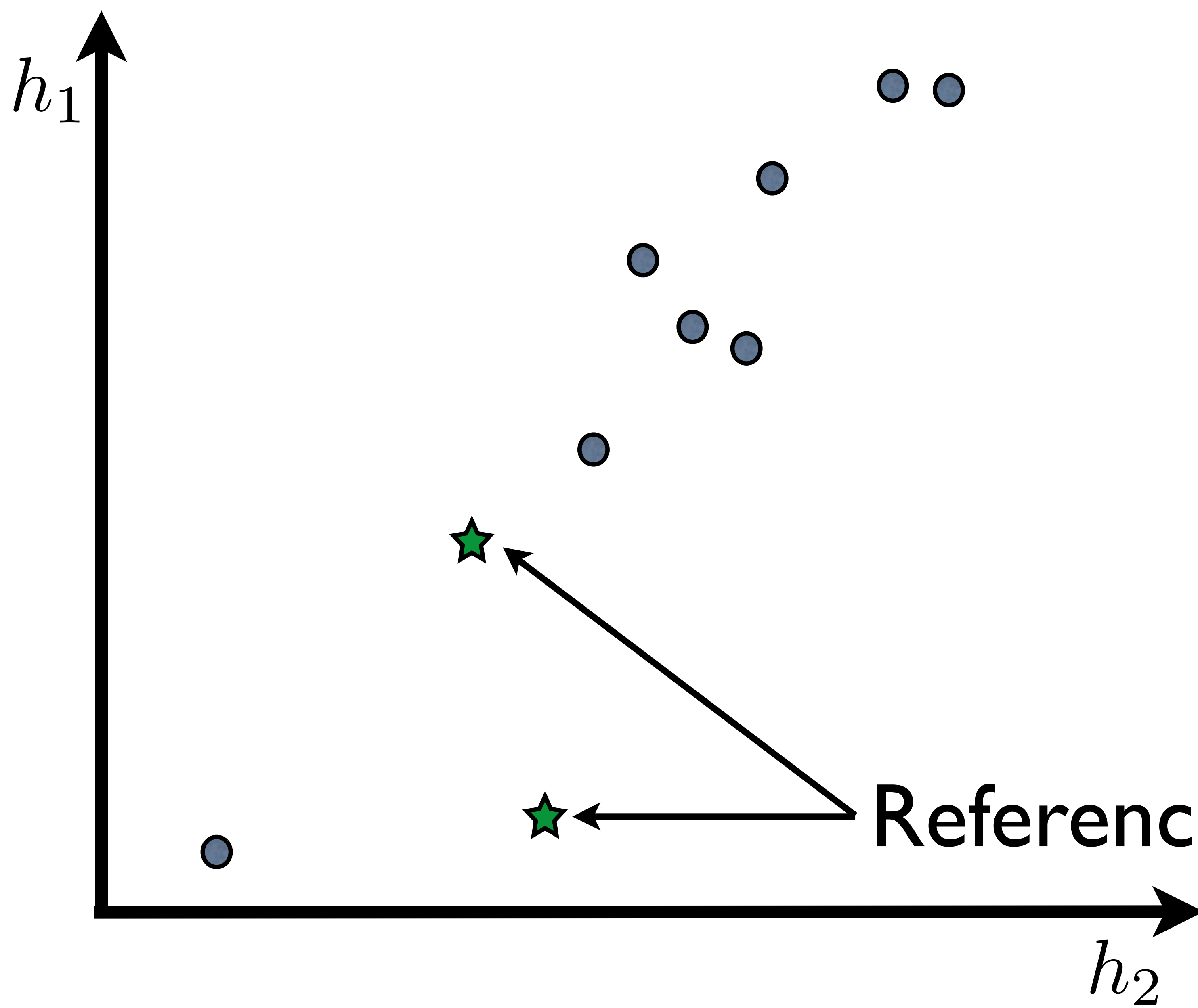
- Improve the modeling capacity of the noisy channel in two ways
  - Reorient the weight vector
  - Add new dimensions (***new features***)
- Questions
  - What features? $\mathbf{h}(\mathbf{g}, \mathbf{e})$
  - How do we set the weights? $\mathbf{w}$

Parameter Learning

Hypothesis Space



Hypothesis Space



Preliminaries

We assume a **decoder** that computes:

$$\langle \mathbf{e}^*, \boxed{\mathbf{a}^*} \rangle = \arg \max_{\langle \mathbf{e}, \boxed{\mathbf{a}} \rangle} \mathbf{w}^\top \mathbf{h}(\mathbf{g}, \mathbf{e}, \boxed{\mathbf{a}})$$

And ***K*-best lists** of, that is:

$$\{\langle \mathbf{e}_i^*, \boxed{\mathbf{a}_i^*} \rangle\}_{i=1}^{i=K} = \arg\, i^{\text{th}}\text{-} \max_{\langle \mathbf{e}, \boxed{\mathbf{a}} \rangle} \mathbf{w}^\top \mathbf{h}(\mathbf{g}, \mathbf{e}, \boxed{\mathbf{a}})$$

Standard, efficient algorithms exist for this.

Cost-Sensitive Training

- Assume we have a **cost function** that gives a score for how good/bad a translation is

$$\ell(\hat{\mathbf{e}}, \mathcal{E}) \mapsto [0, 1]$$

- Optimize the weight vector by making reference to this function
    - We will talk about two ways to do this

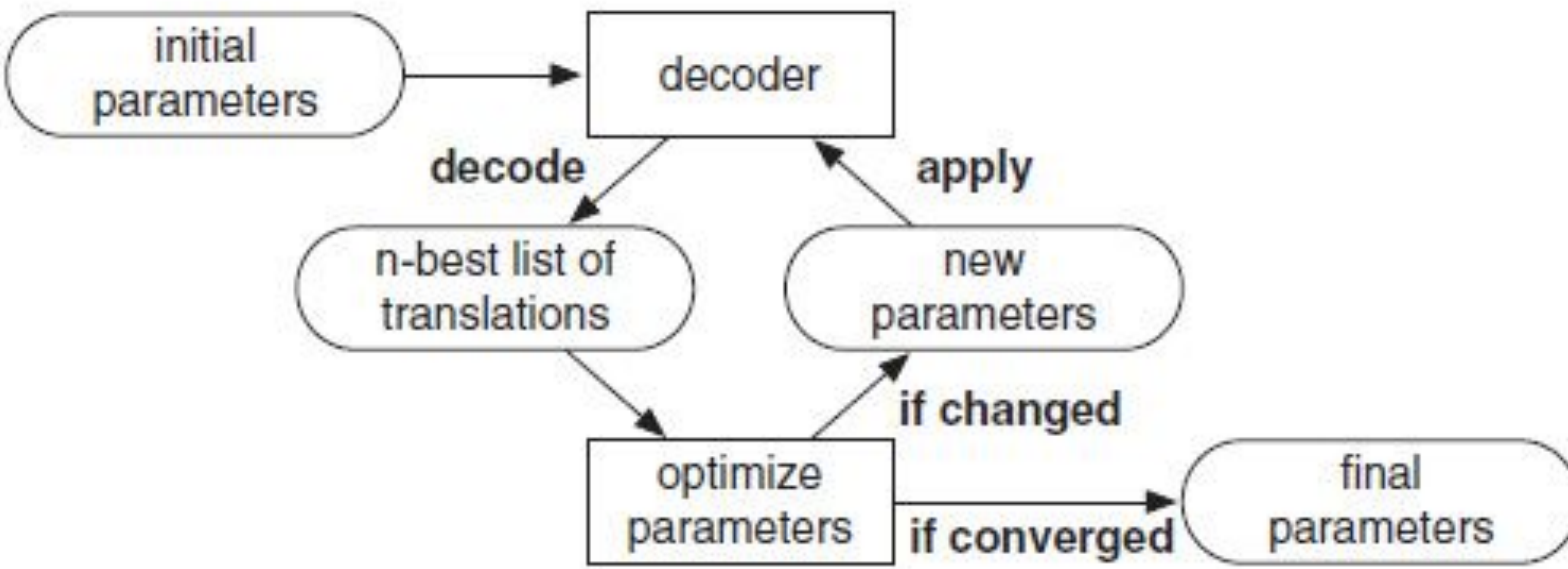
MERT

- **M**inimum **E**rror **R**ate **T**raining
- Directly optimize for an automatic evaluation metric instead of likelihood
- Maximize the BLEU score on a **held out development set**
- Iteratively update the parameters by re-scoring n-best lists and comparing the highest scoring translation to the reference

MERT

- Even with 10-15 features it's not possible to exhaustively search the space of possible feature values
- We need a good heuristic method to search the space
- Another problem: the initial parameters might be so bad that the original n-best list is not a good sample of the translations

Iterative parameter tuning



Powell Search

- Explore a high-dimensional space by finding a better point along one line in the space
- Simplest form: Vary one parameter at a time
- If the optimal value is better than the current value, then change it and move to the next parameter
- Iterate until there are no single parameter updates that increase the score

Powell Search

- Problem: searching for the best value for a single parameter is still daunting
  - Parameters are real-valued #s, so they have an infinite number of possible values
- Key insight of MERT: only a small number of threshold values will change the 1-best translation
  - Only 1-best translations change BLEU

Finding the threshold points for 1 sentence

Given weight vector $\mathbf{w}$, any hypothesis $\langle \mathbf{e}, \mathbf{a} \rangle$ will have a (scalar) score $m = \mathbf{w}^\top \mathbf{h}(\mathbf{g}, \mathbf{e}, \mathbf{a})$

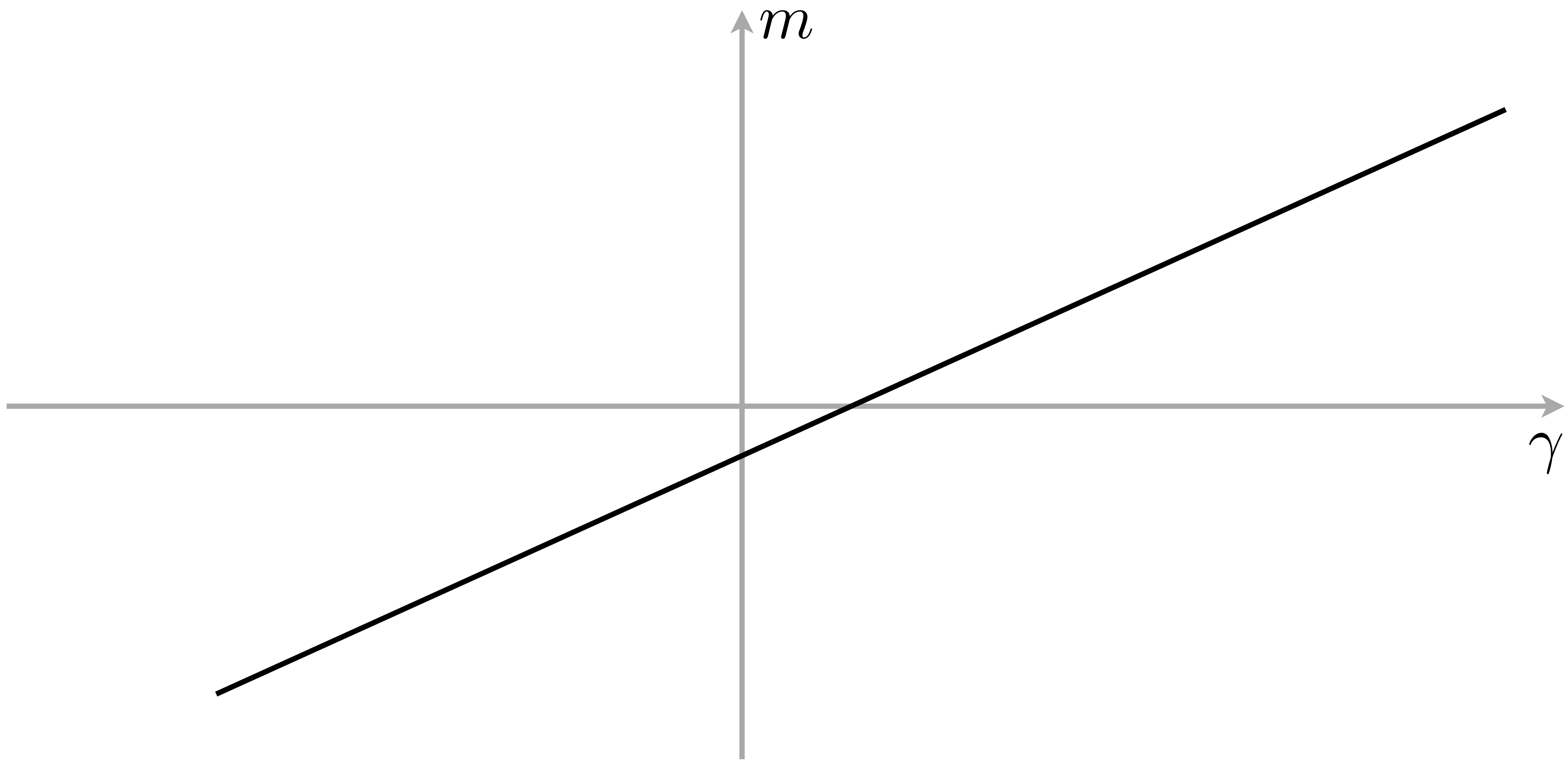
Now pick a **search vector v**, and consider how the score of this hypothesis will change:

$$\begin{aligned} \mathbf{w}_{\text{new}} &= \mathbf{w} + \gamma \mathbf{v} \\ m &= (\mathbf{w} + \gamma \mathbf{v})^\top \mathbf{h}(\mathbf{g}, \mathbf{e}, \mathbf{a}) \\ &= \underbrace{\mathbf{w}^\top \mathbf{h}(\mathbf{g}, \mathbf{e}, \mathbf{a})}_{b} + \gamma \underbrace{\mathbf{v}^\top \mathbf{h}(\mathbf{g}, \mathbf{e}, \mathbf{a})}_{a} \end{aligned}$$

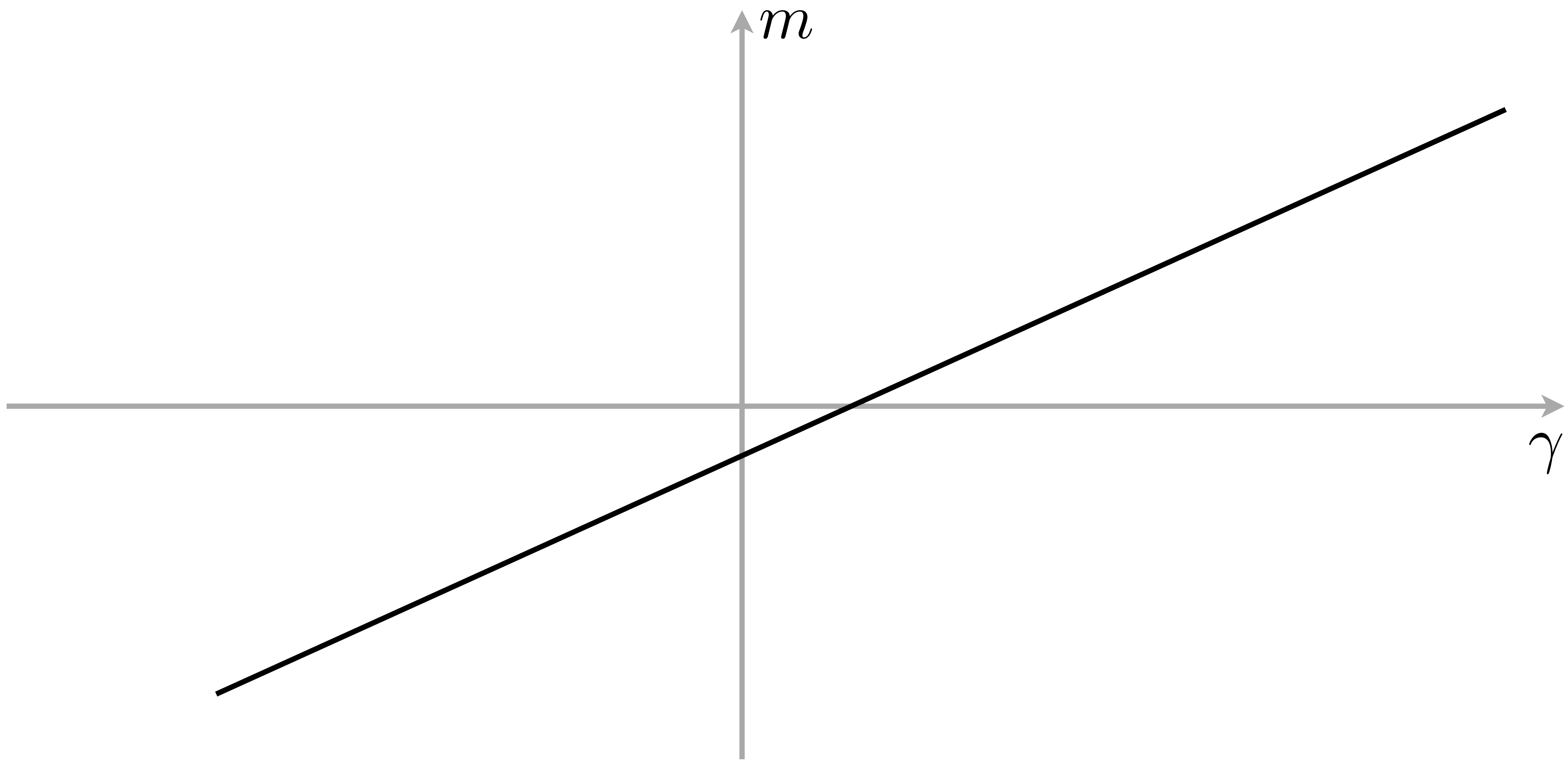
$$\boxed{m = a\gamma + b}$$

Linear function in 2D!

MERT

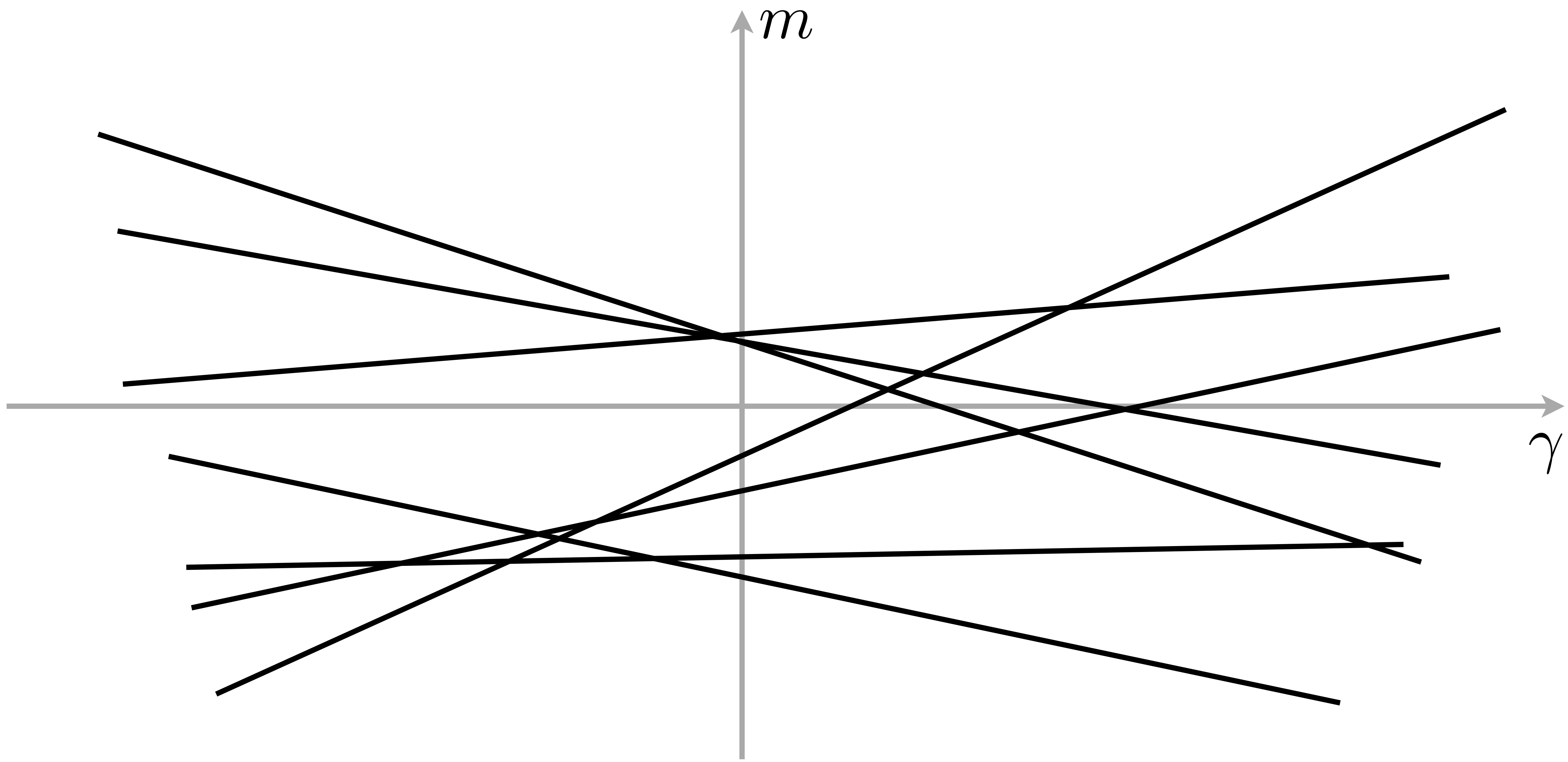


MERT



Recall our k-best set $\{\langle \mathbf{e}_i^*, \mathbf{a}_i^* \rangle\}_{i=1}^K$

MERT



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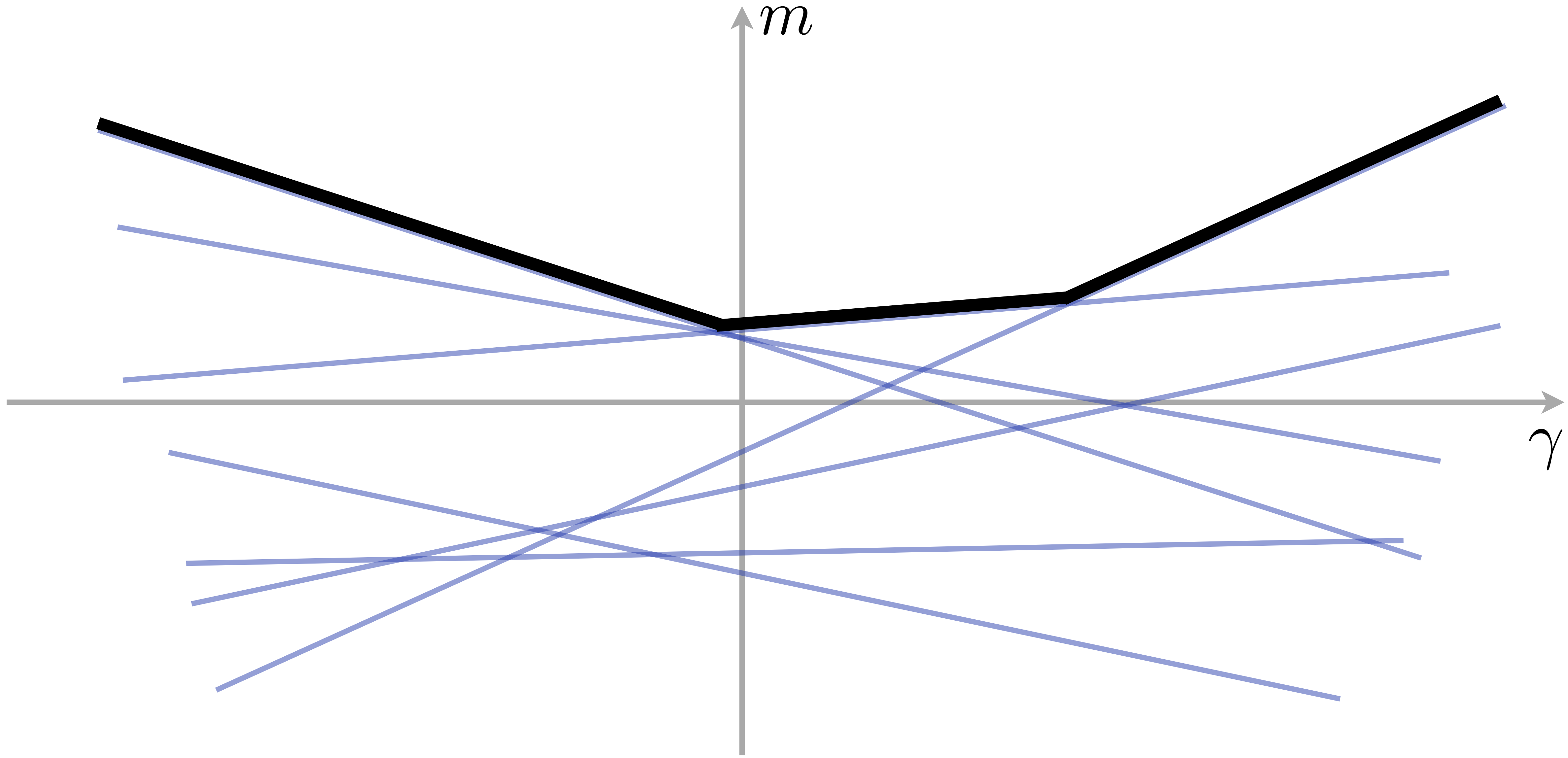
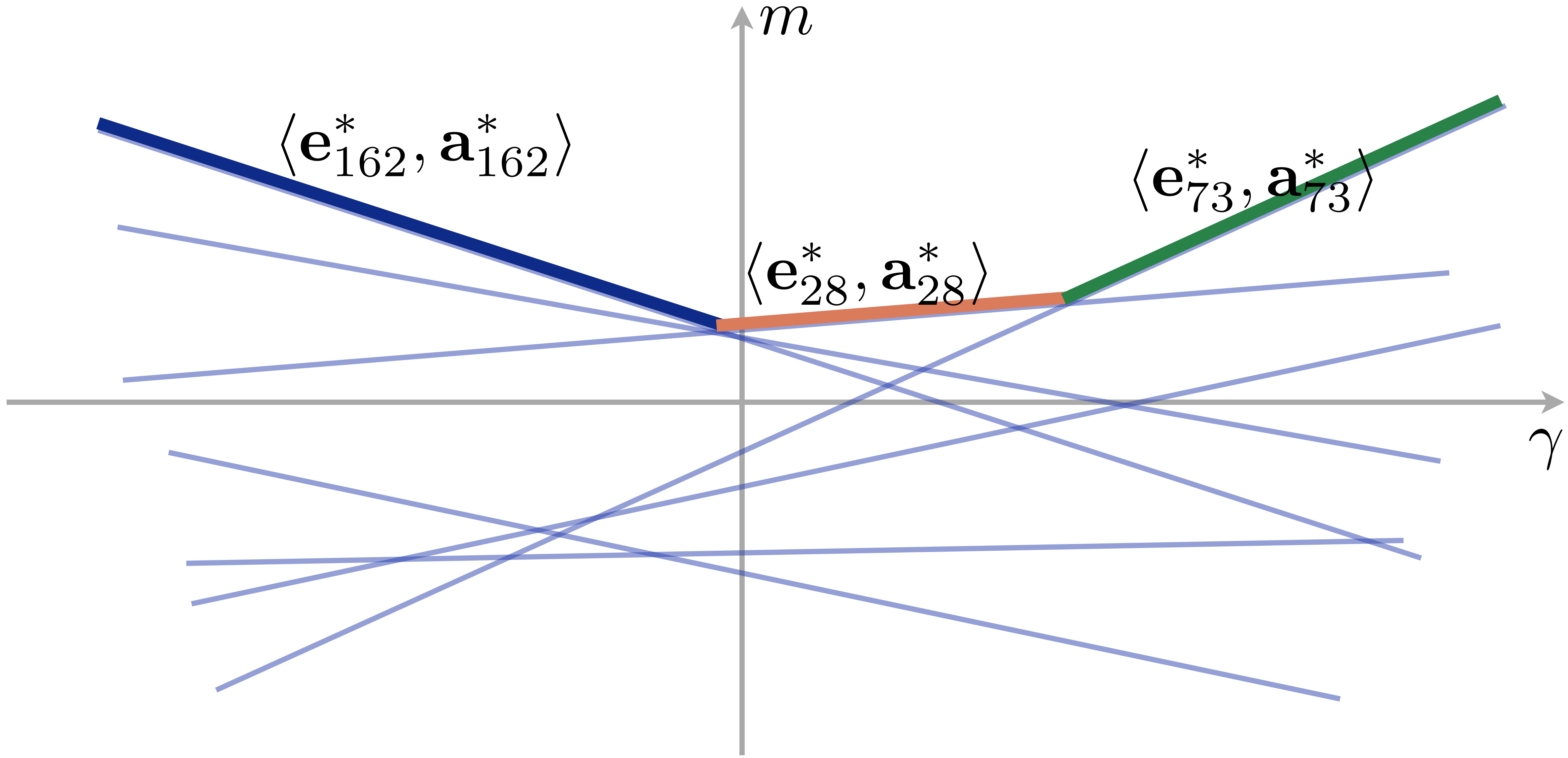
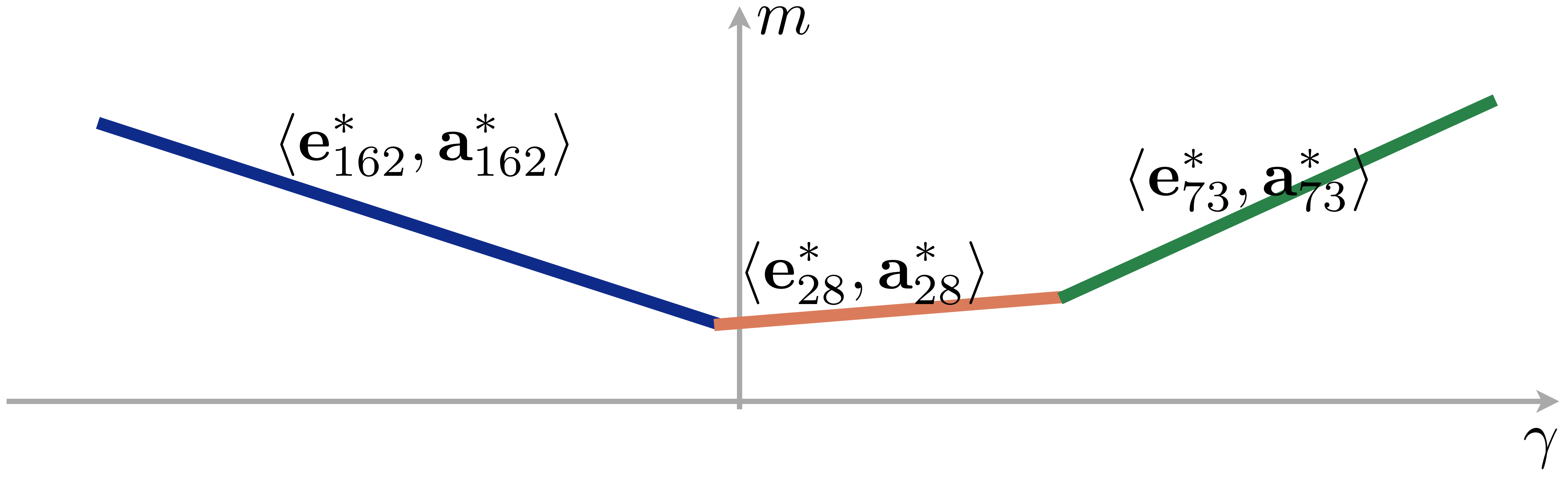
MERT



MERT


m
$\langle \mathbf{e}^*_{162}, \mathbf{a}^*_{162} \rangle$
$\langle \mathbf{e}^*_{73}, \mathbf{a}^*_{73} \rangle$
$\langle \mathbf{e}^*_{28}, \mathbf{a}^*_{28} \rangle$
γ

MERT



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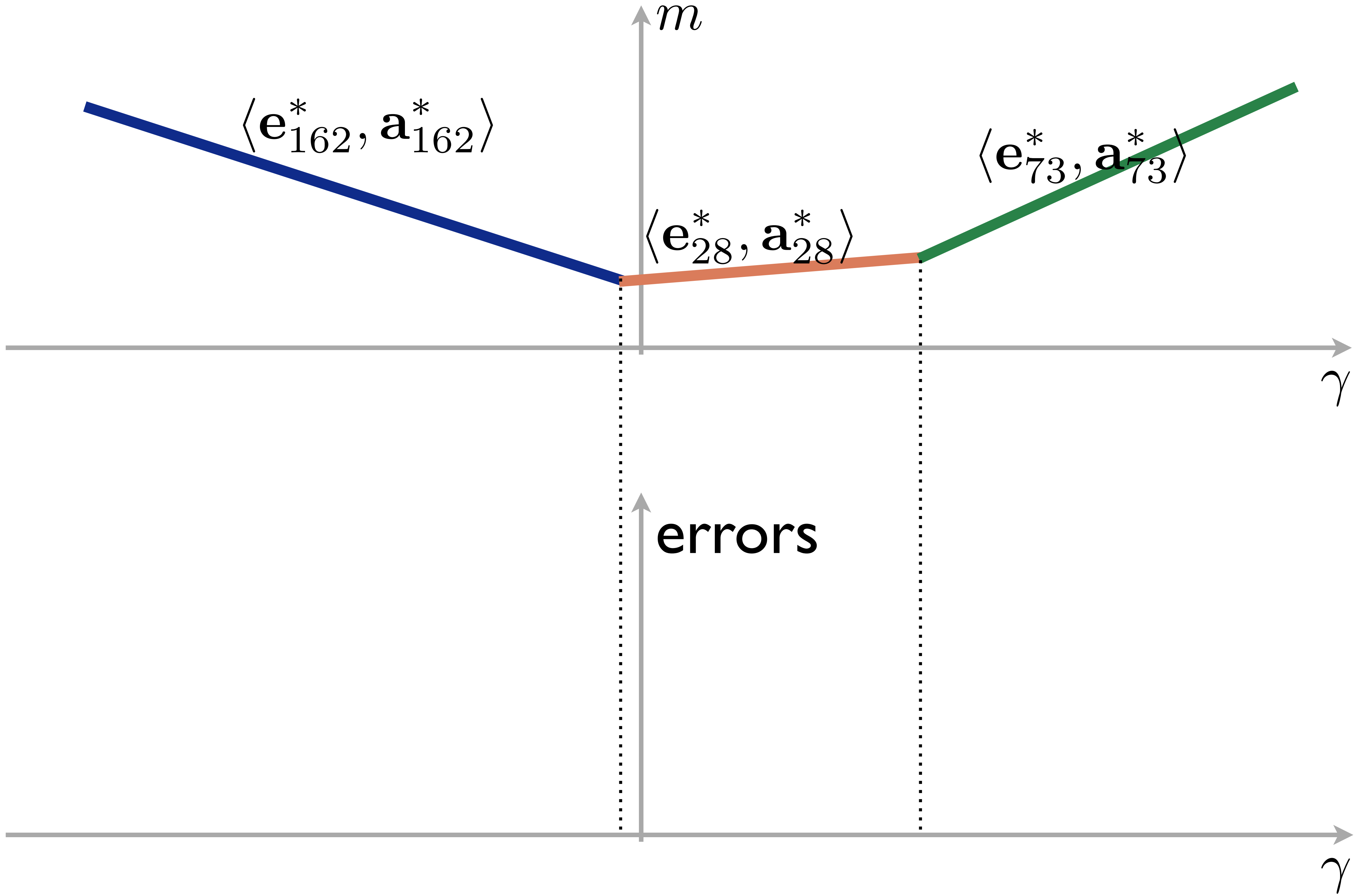

m
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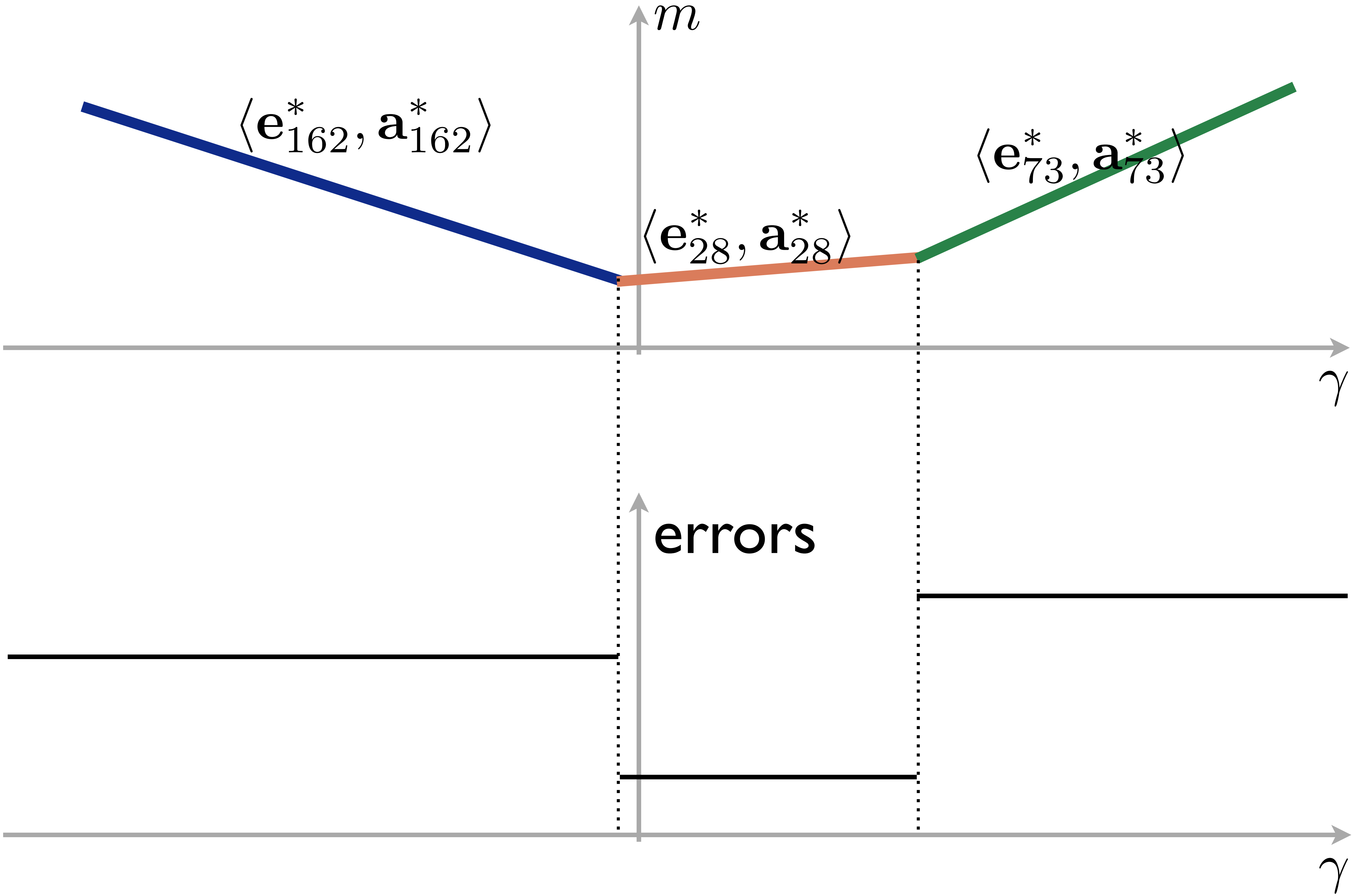
$\langle \mathbf{e}^*_{28}, \mathbf{a}^*_{28} \rangle$
$\langle \mathbf{e}^*_{73}, \mathbf{a}^*_{73} \rangle$
γ
errors
γ

MERT



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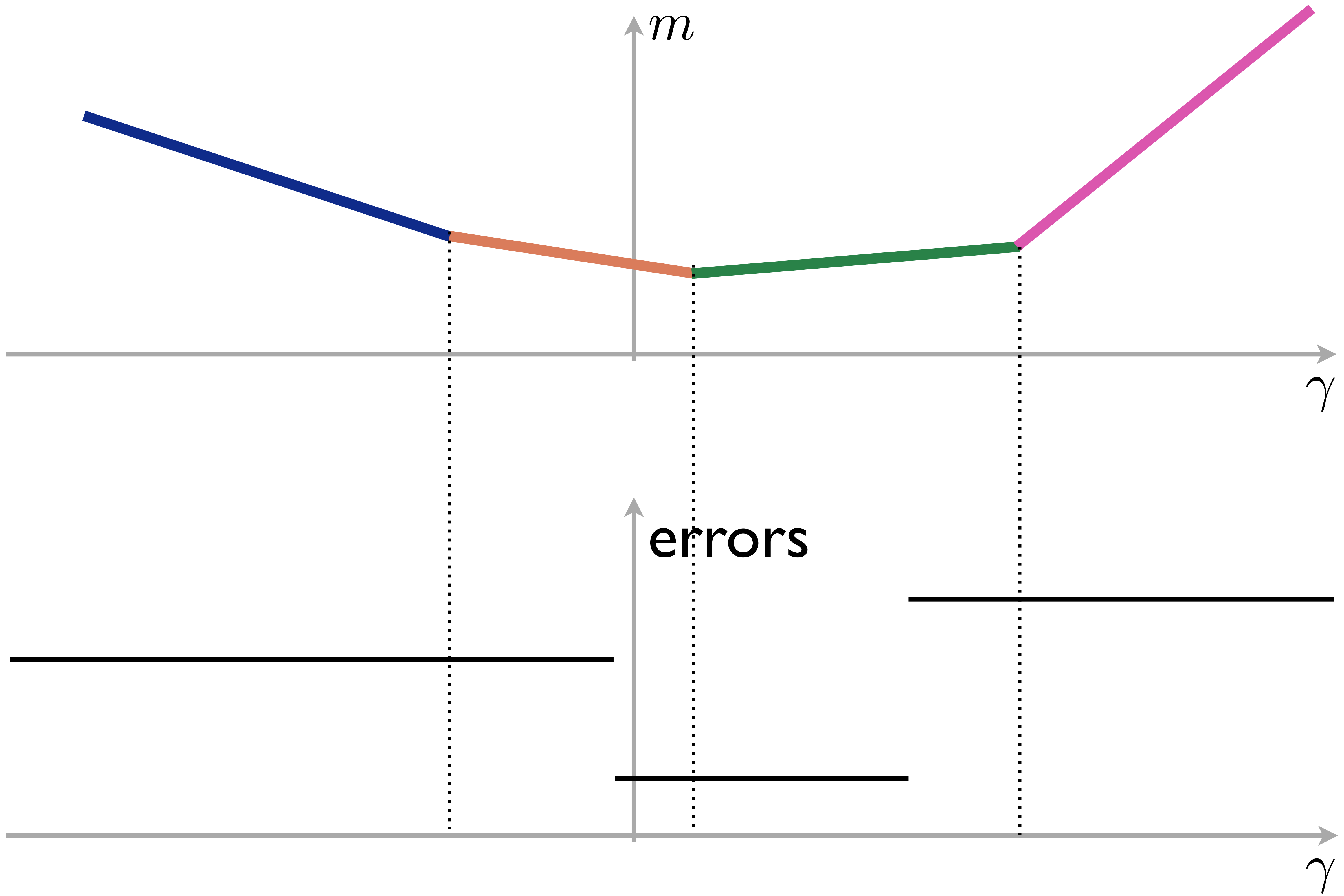
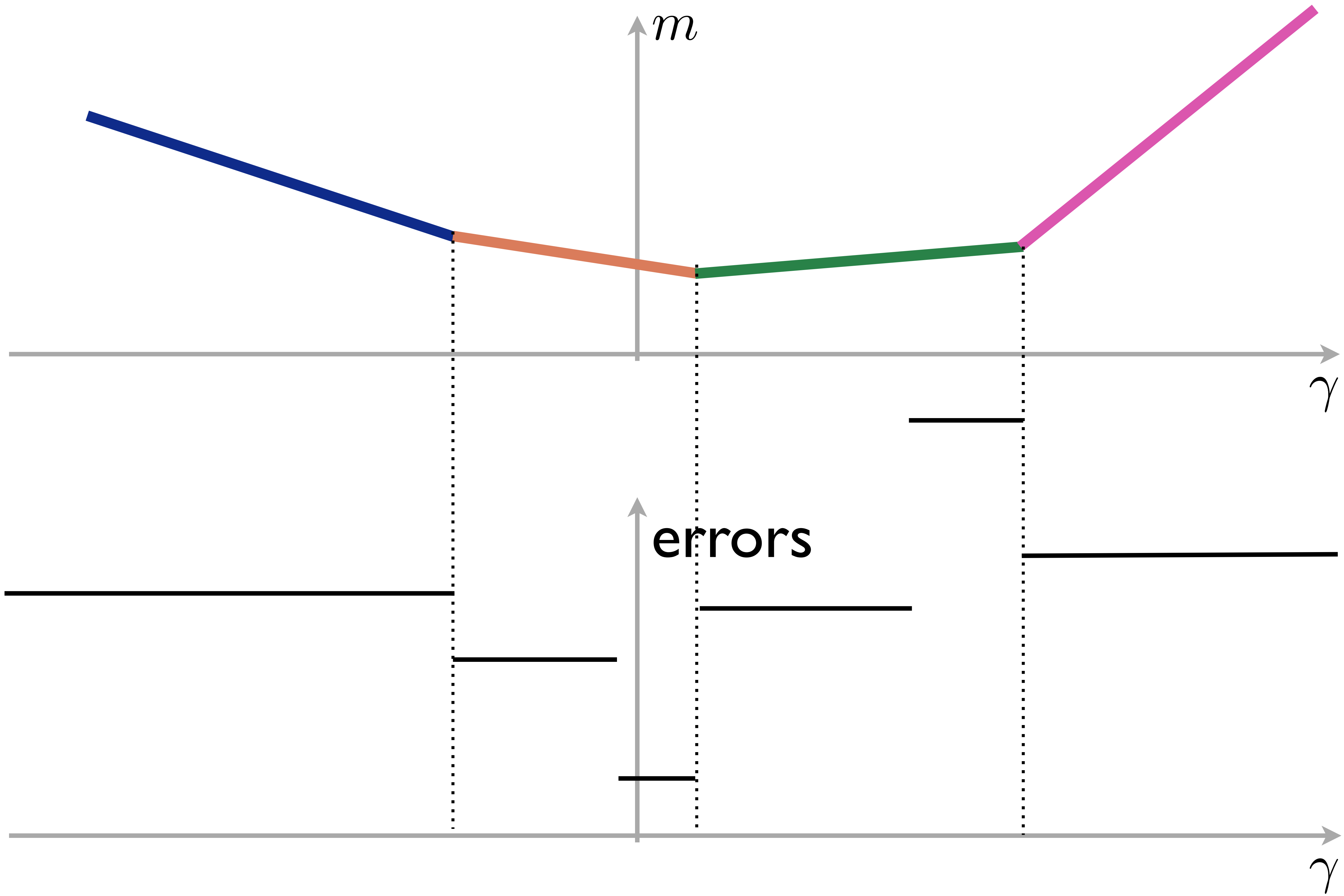
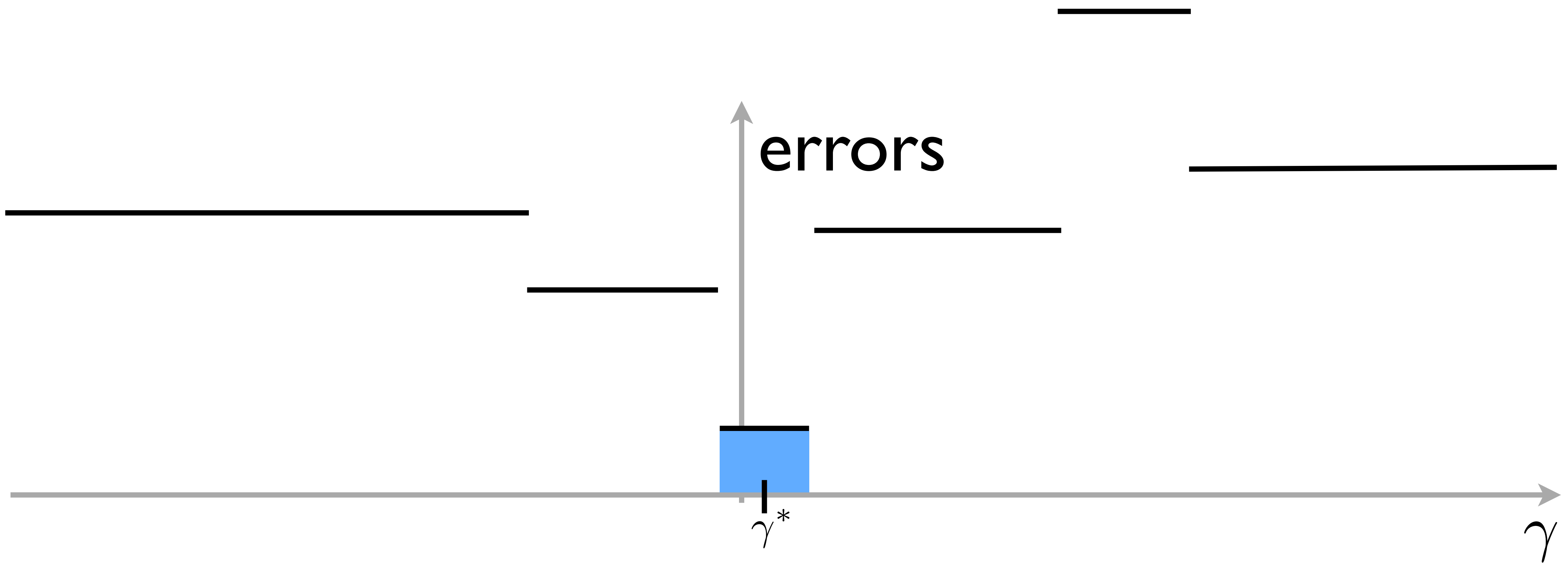
MERT



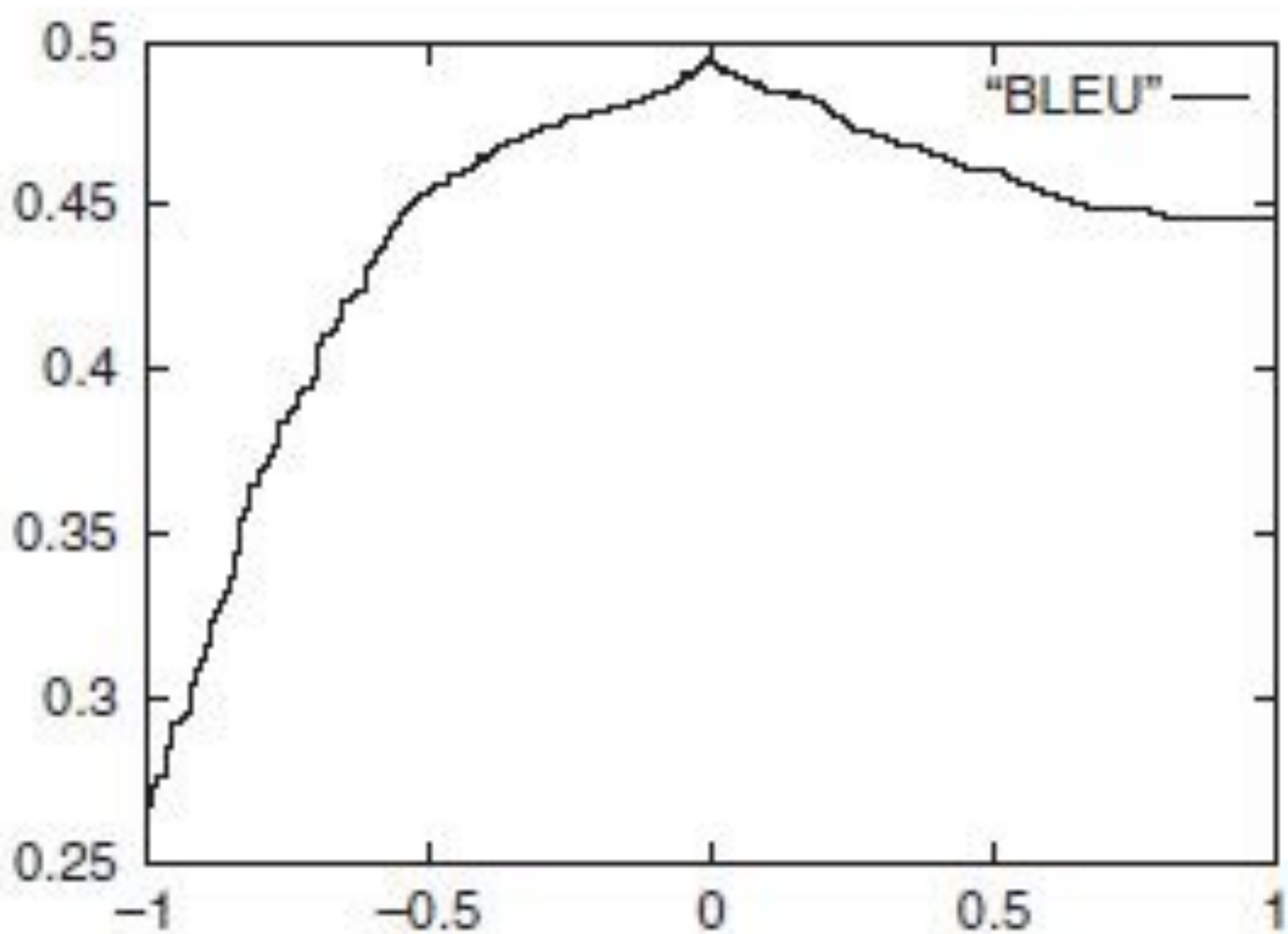
MERT





Let $\mathbf{w}_{\mathrm{new}} = \gamma^* \mathbf{v} + \mathbf{w}$

The effect on BLEU varying one parameter



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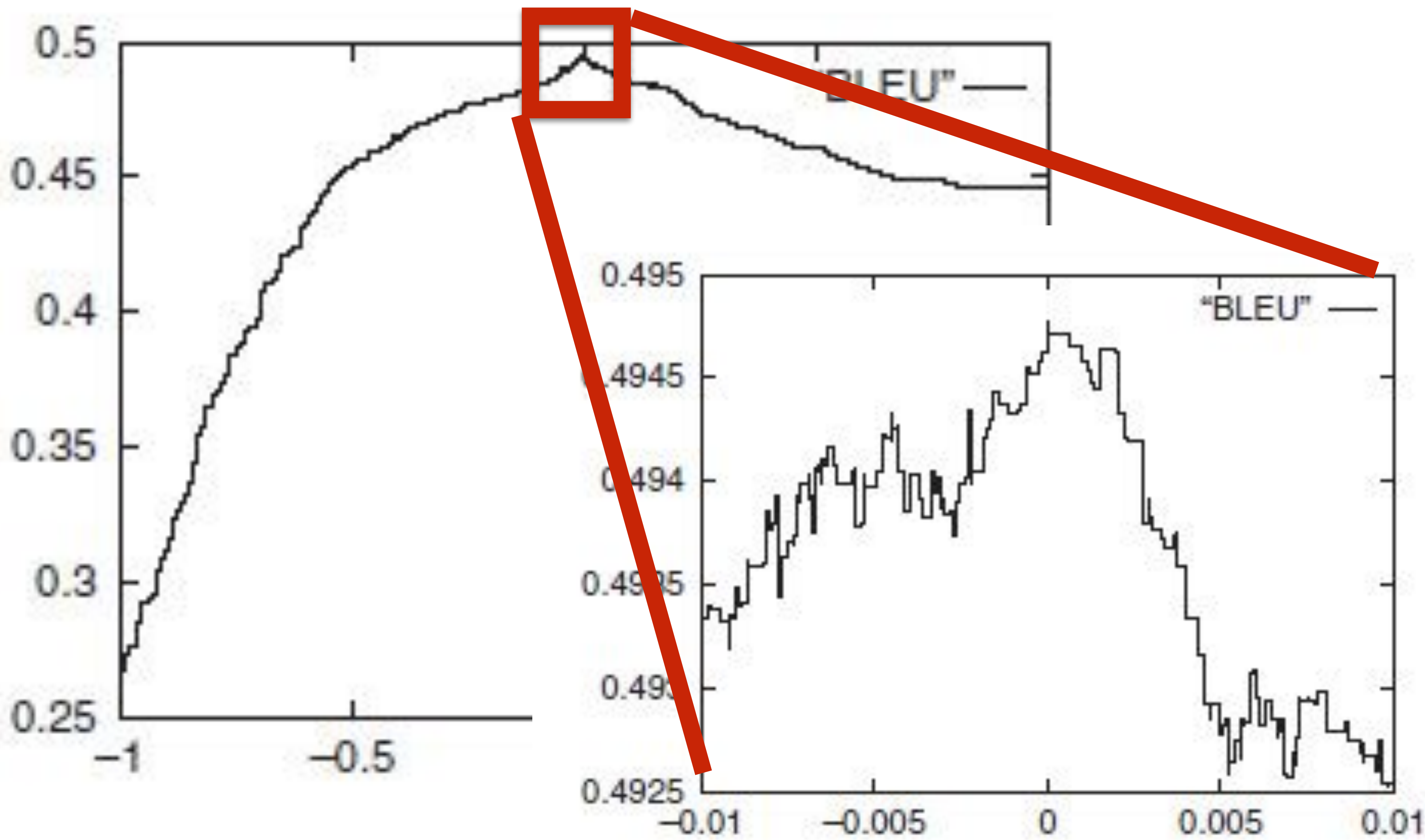
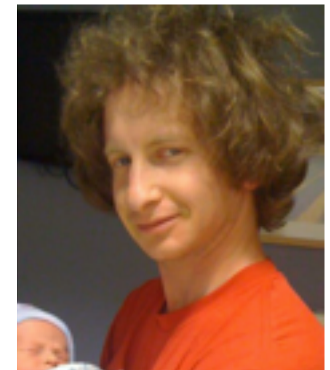
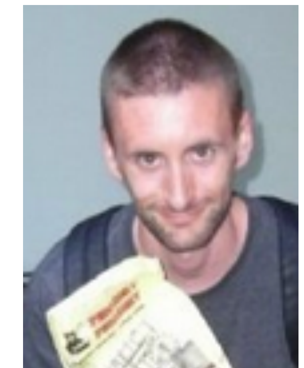


MERT

- Minimum error rate training
  - Can maximize or minimize!
- In practice "errors" are sufficient statistics for evaluation metrics (e.g., BLEU, AMBER, TER, etc)
- Downside: MERT can only be used to optimize a small handful of features

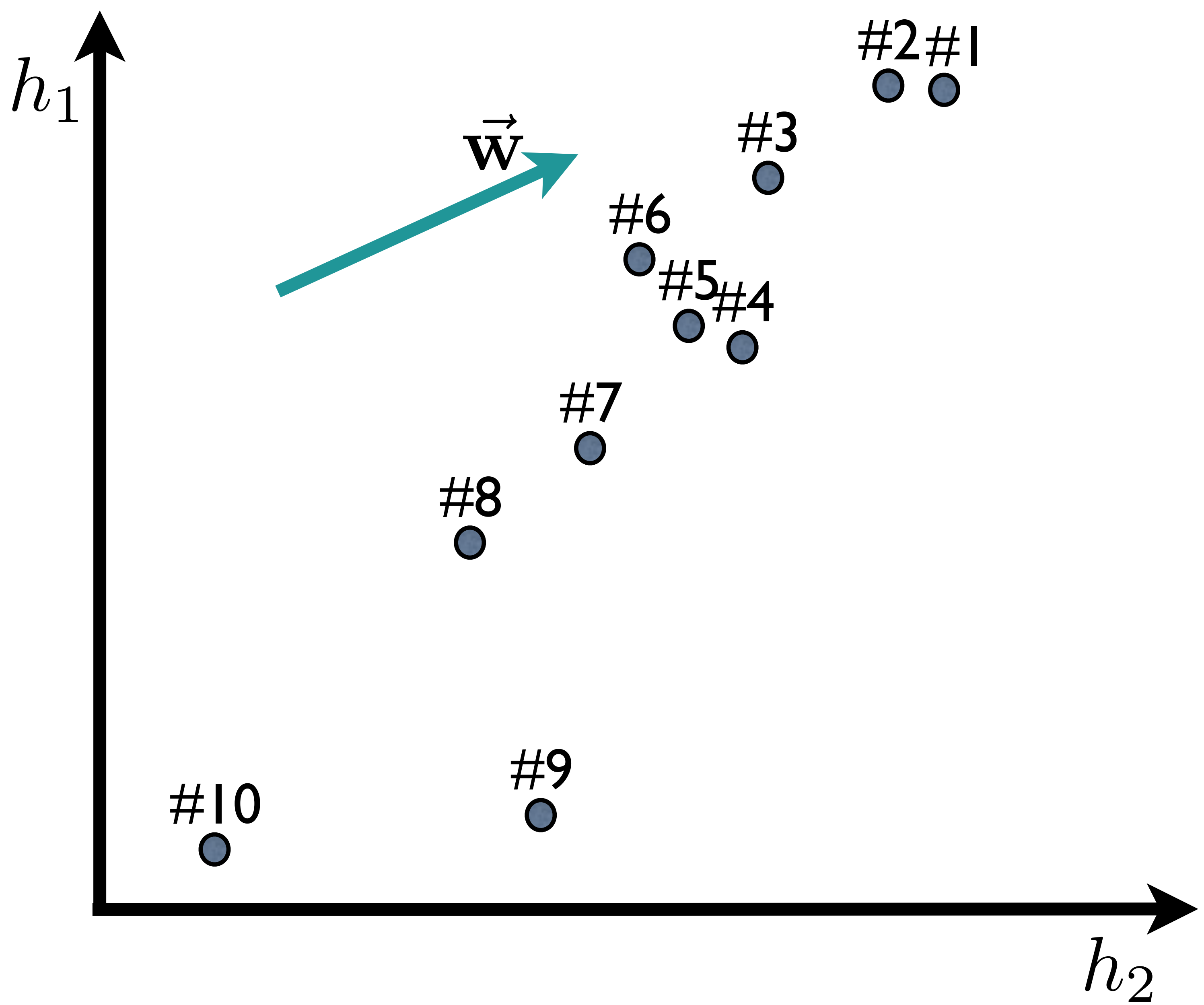
Training as Classification





- **P**airwise **R**anking **O**ptimization
  - Reduce training problem to **binary classification** with a **linear model**
- **Algorithm**
  - For i=1 to N
    - Pick random pair of hypotheses (A,B) from K-best list
    - Use cost function to determine if is A or B better
    - Create ith training instance
  - Train binary linear classifier

K-Best List Example



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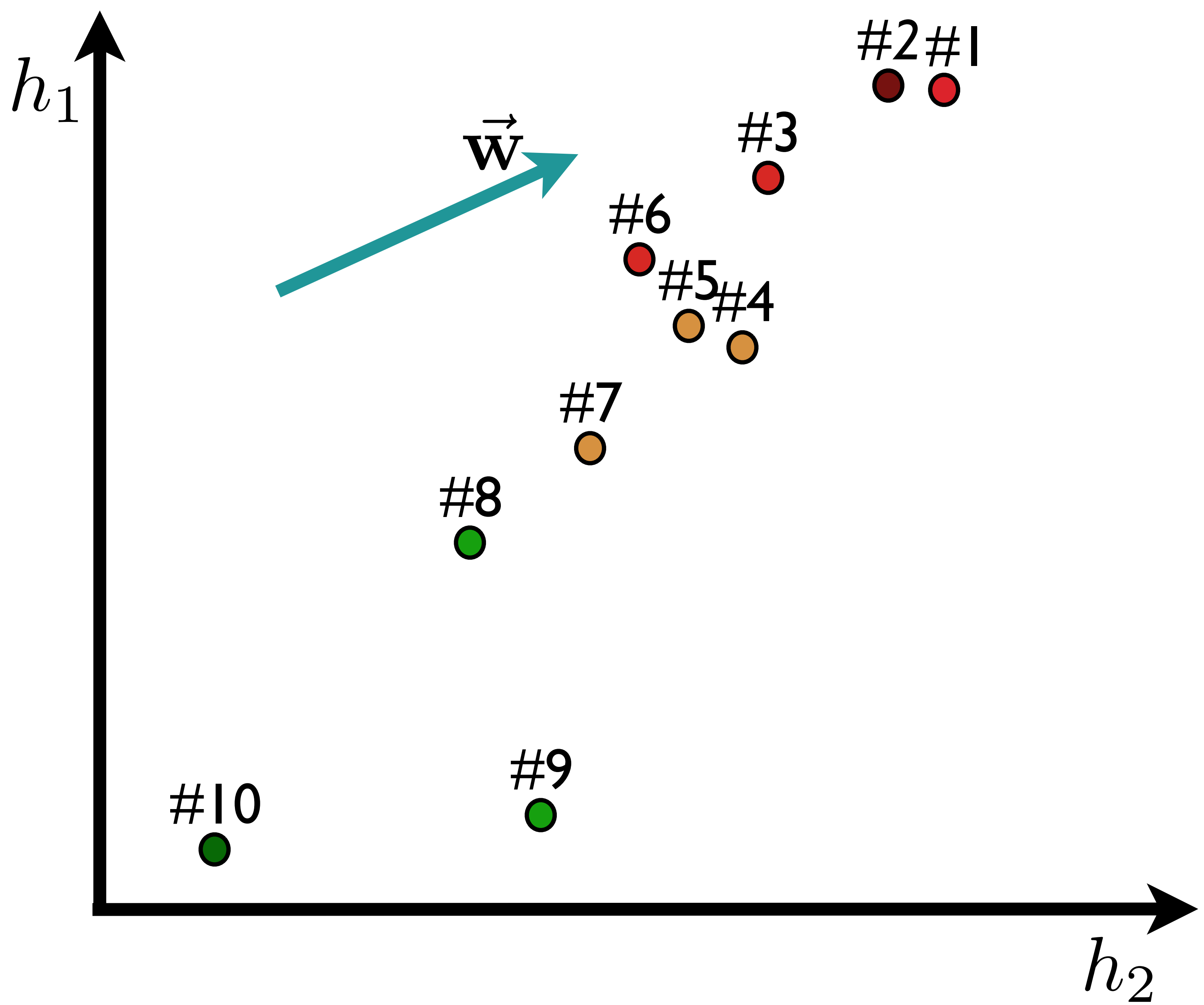

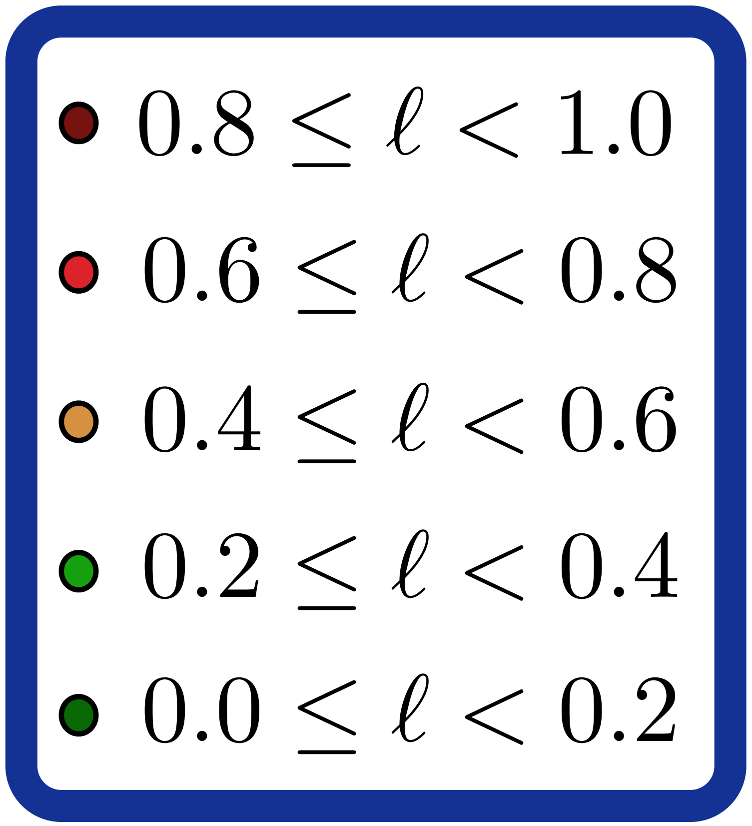

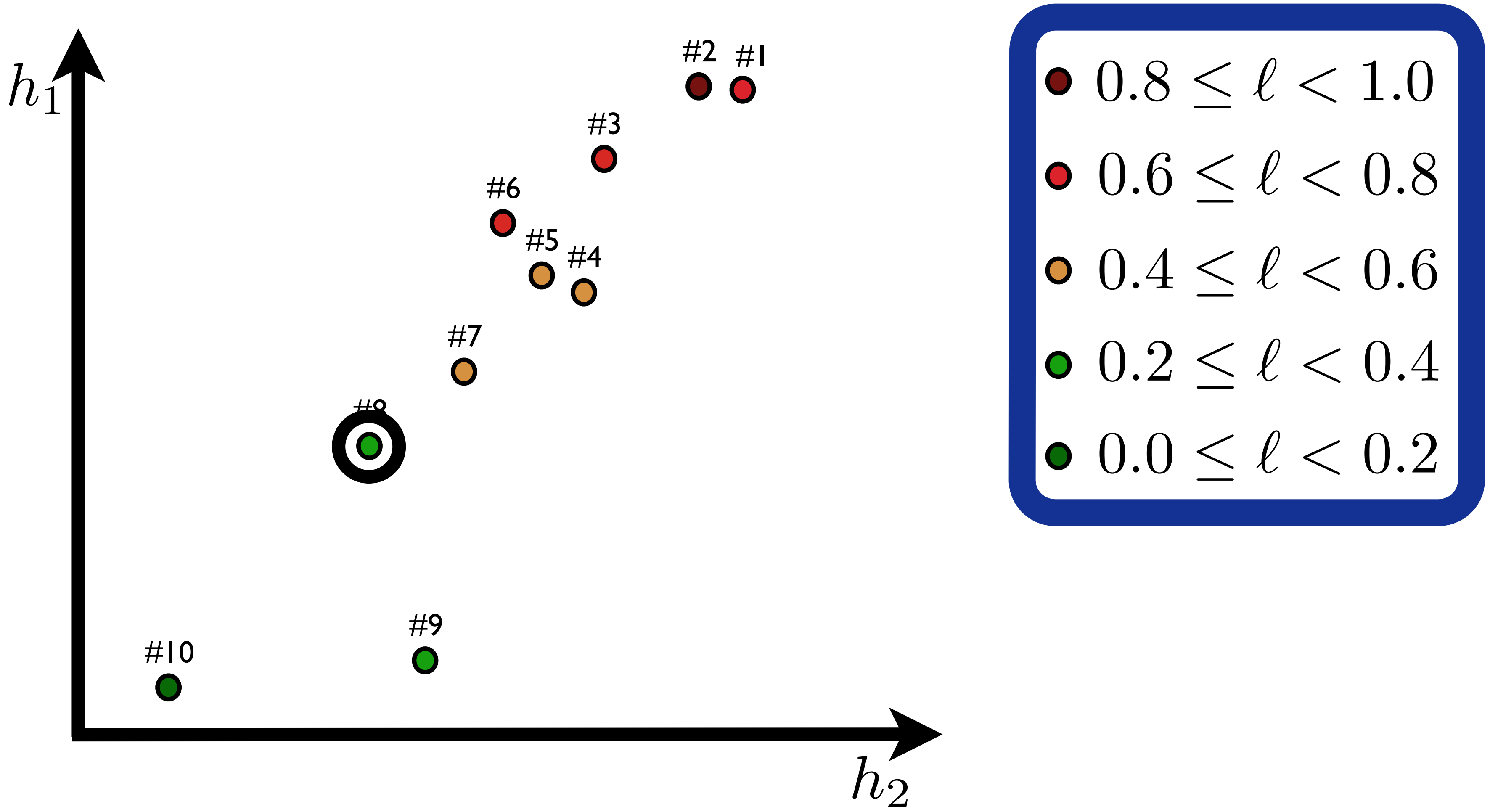

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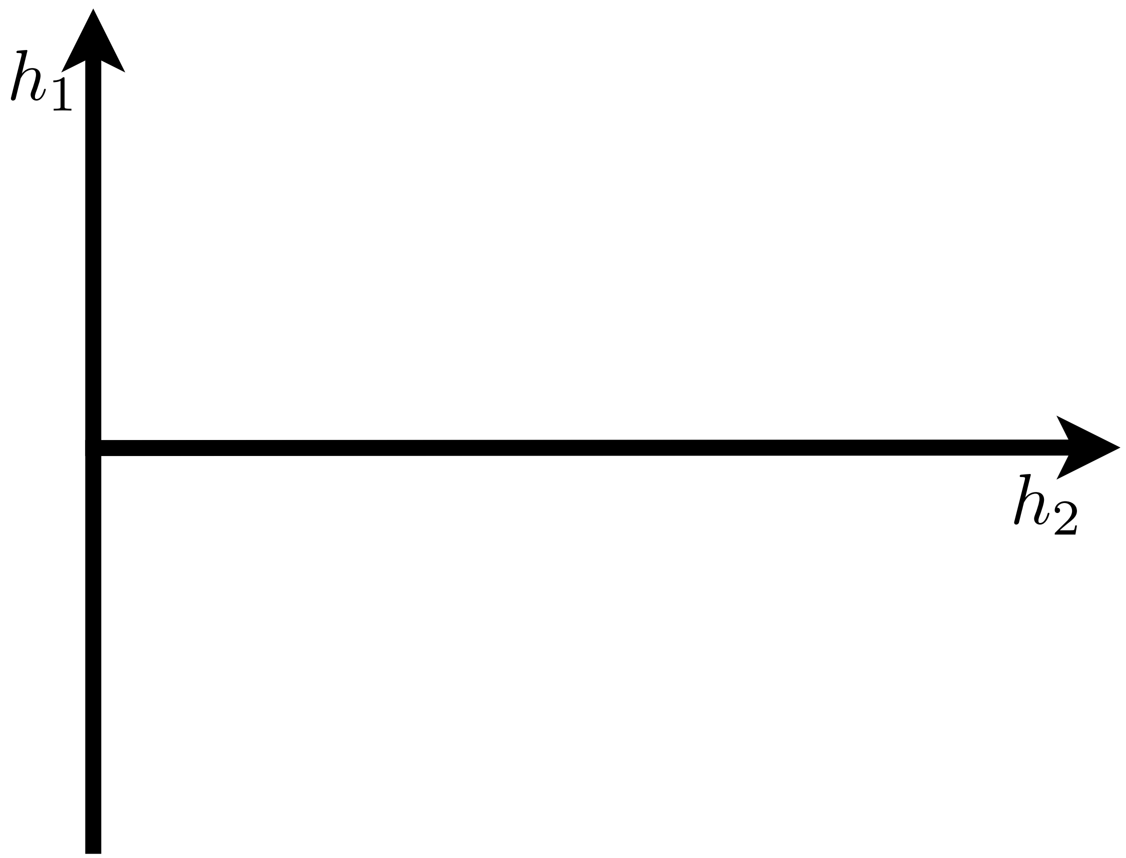

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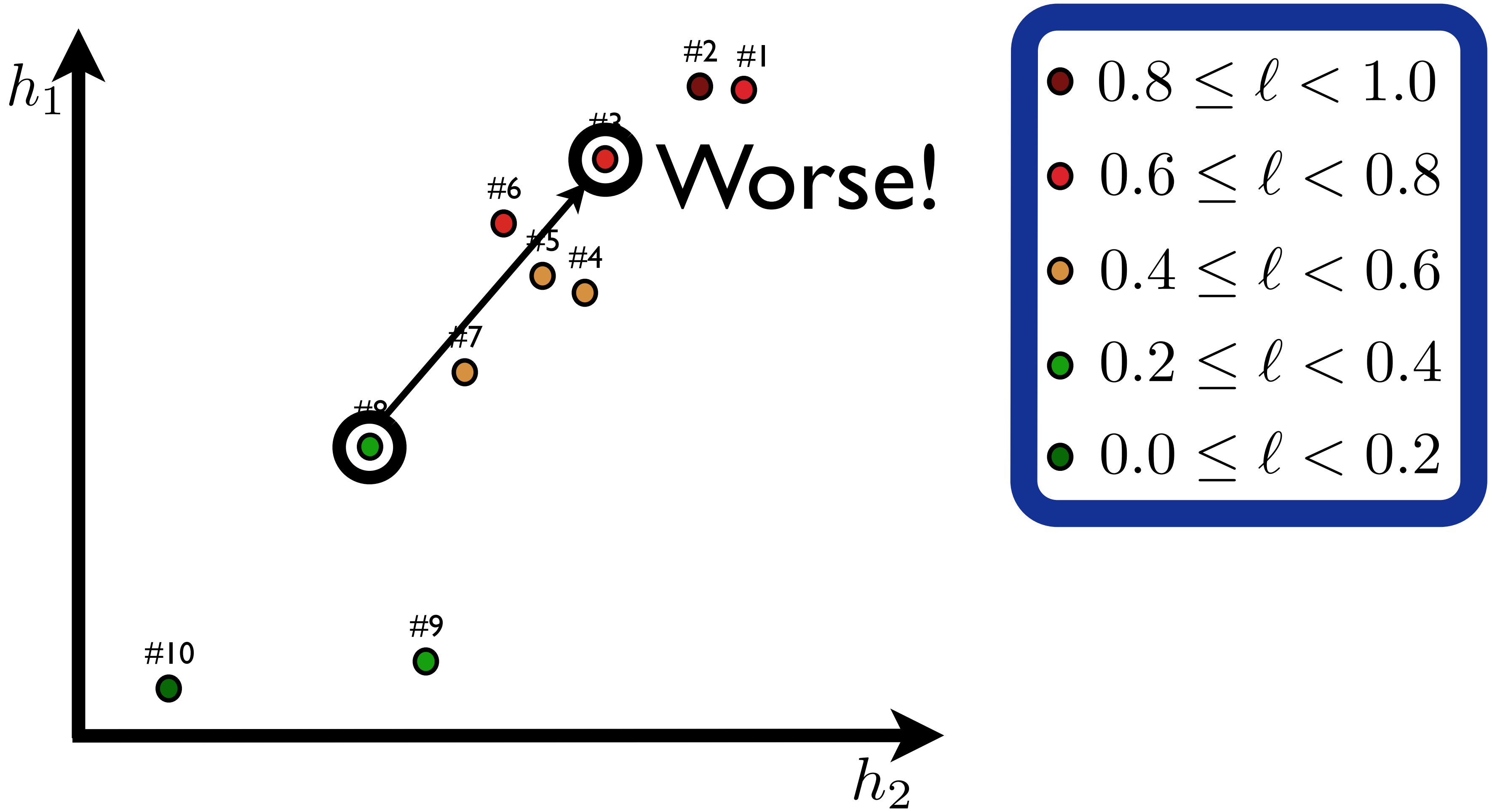

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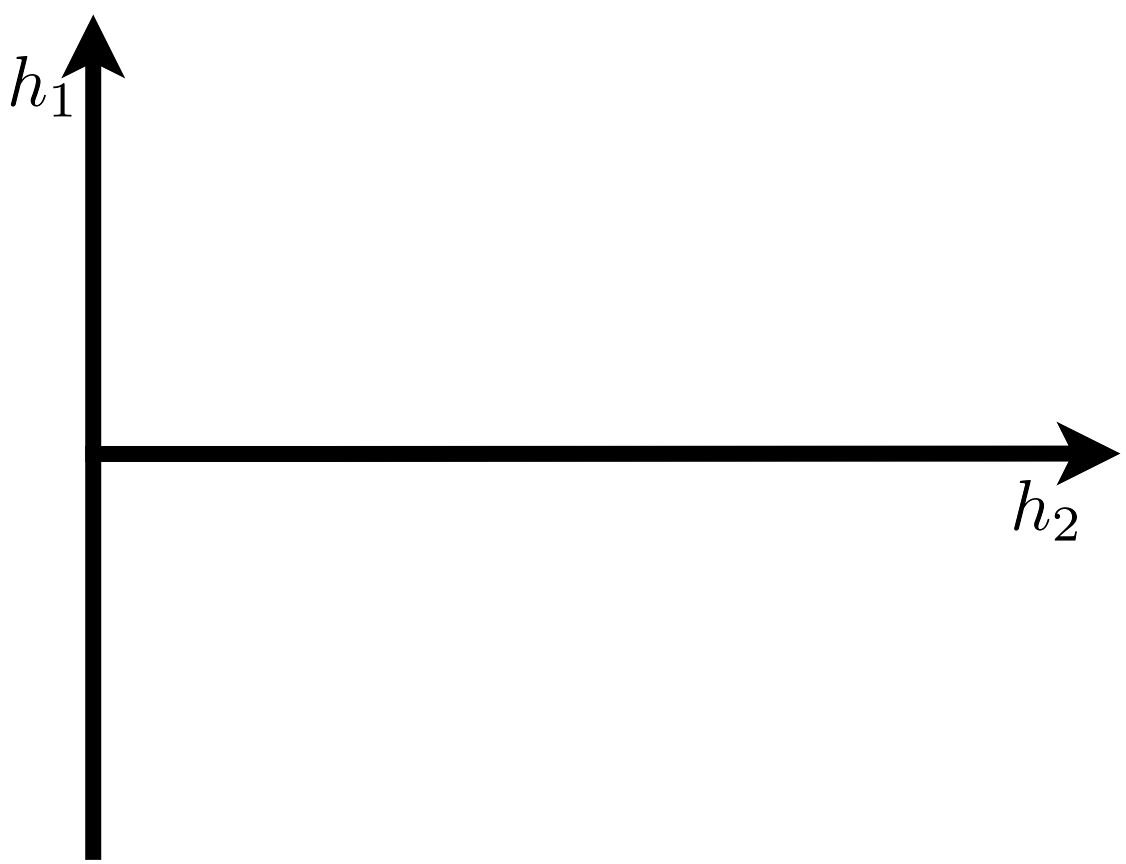

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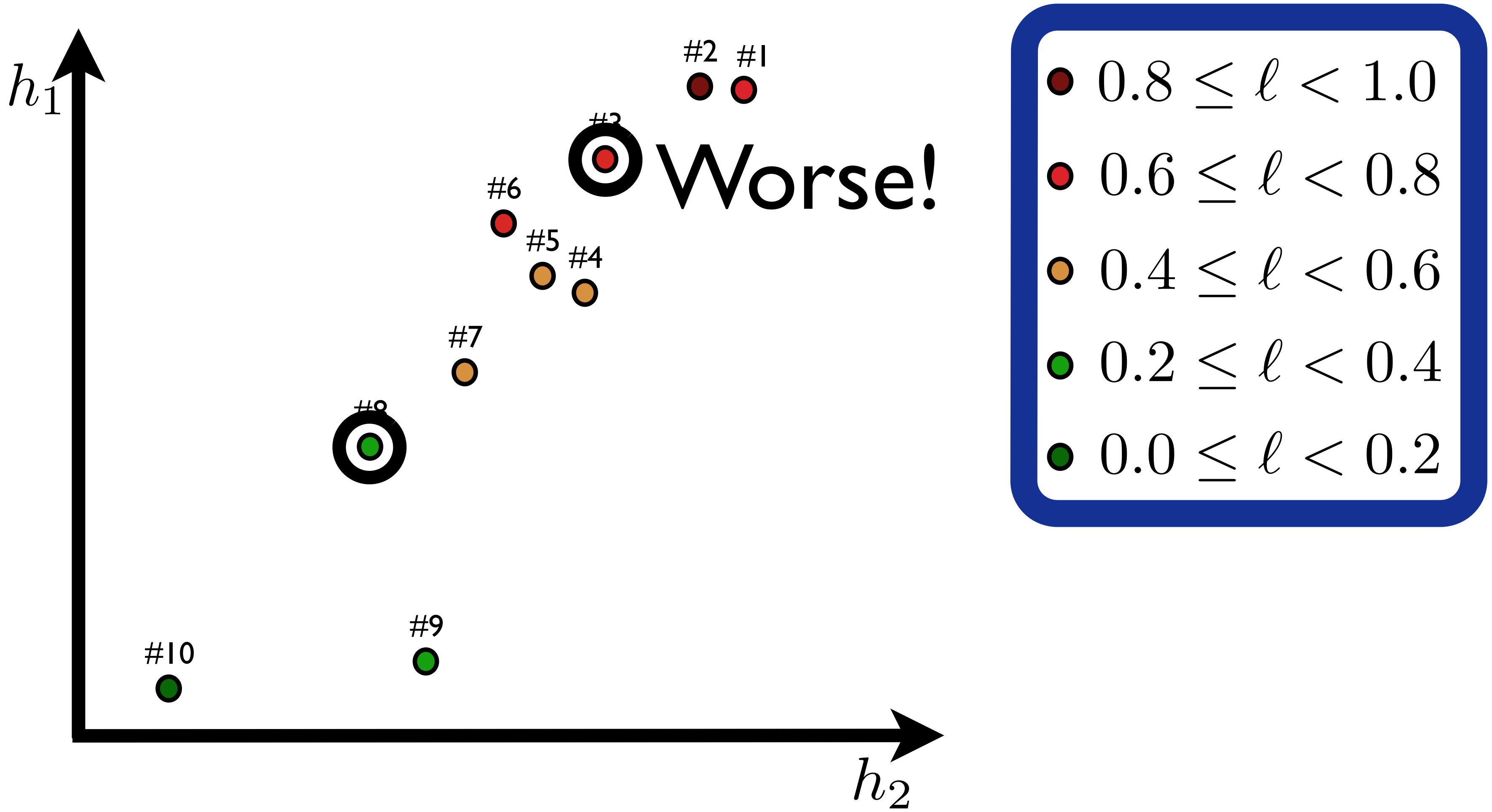

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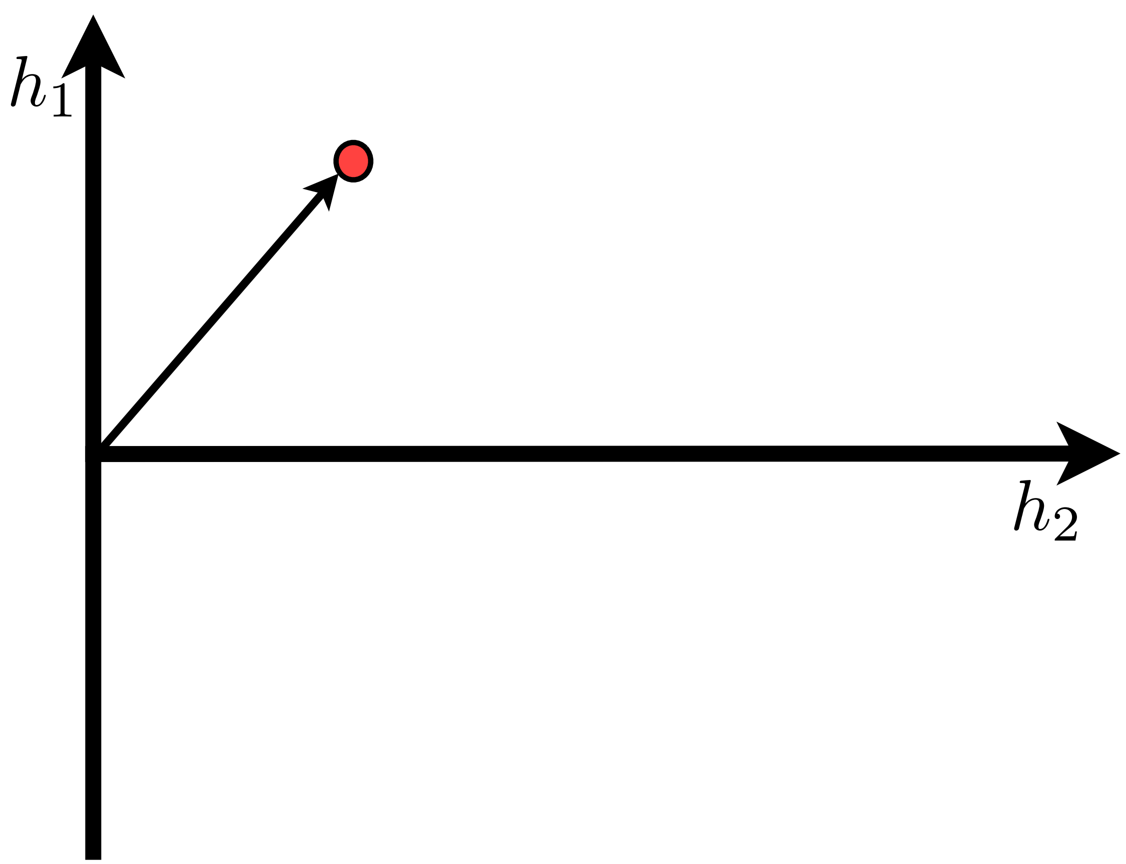

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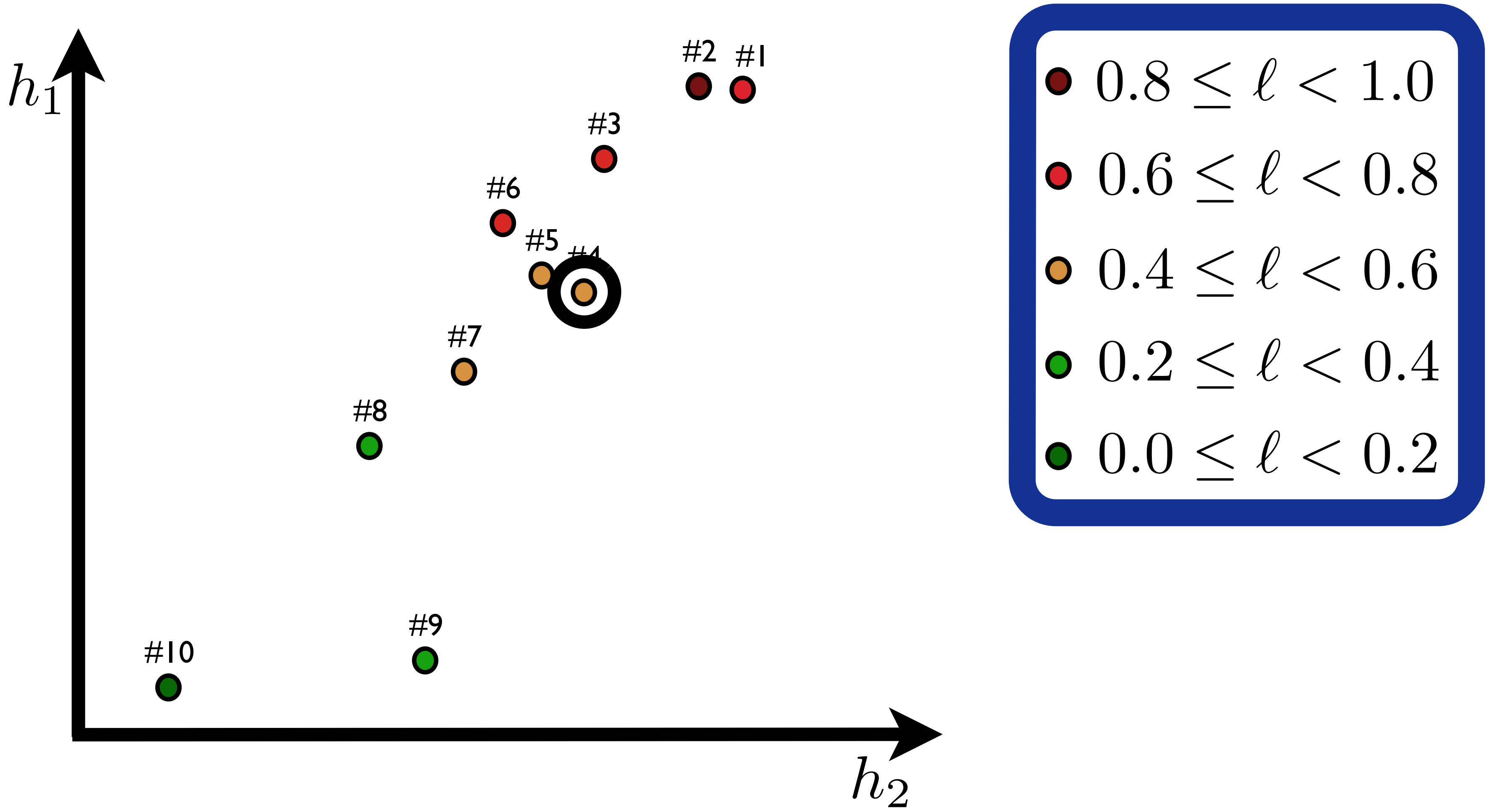
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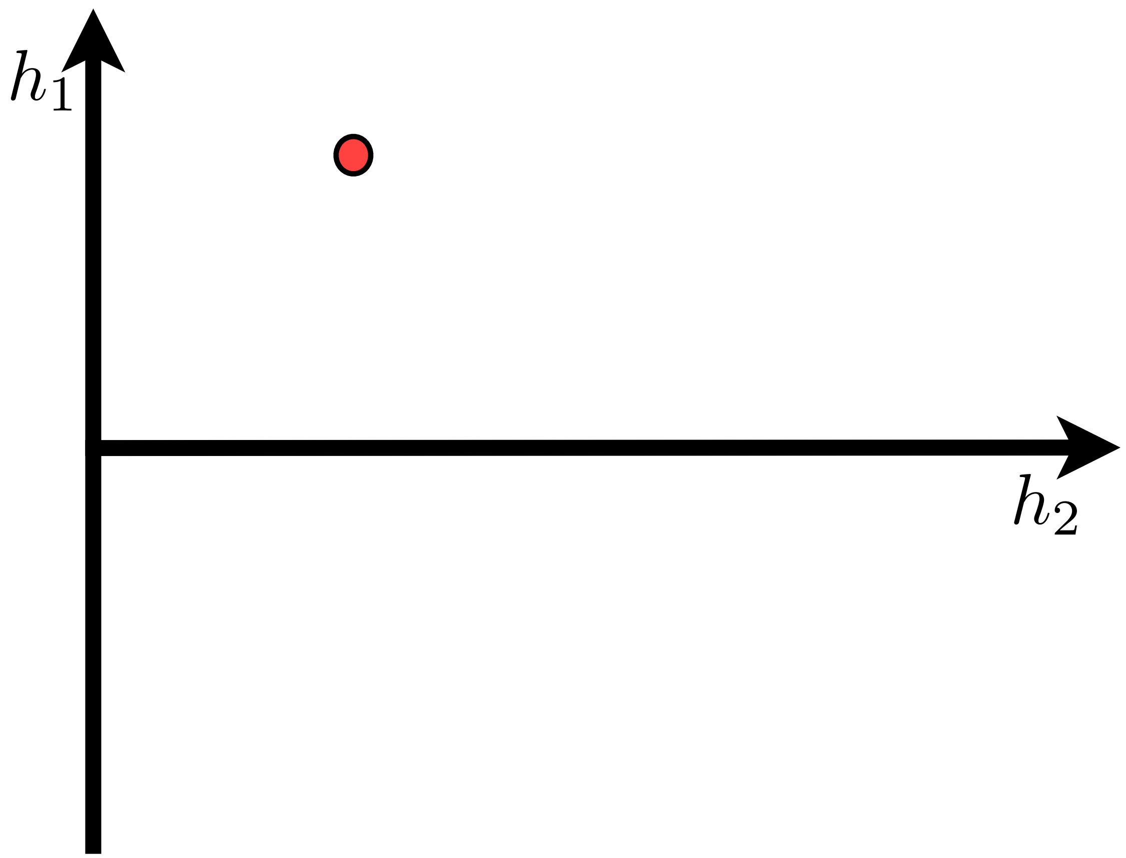
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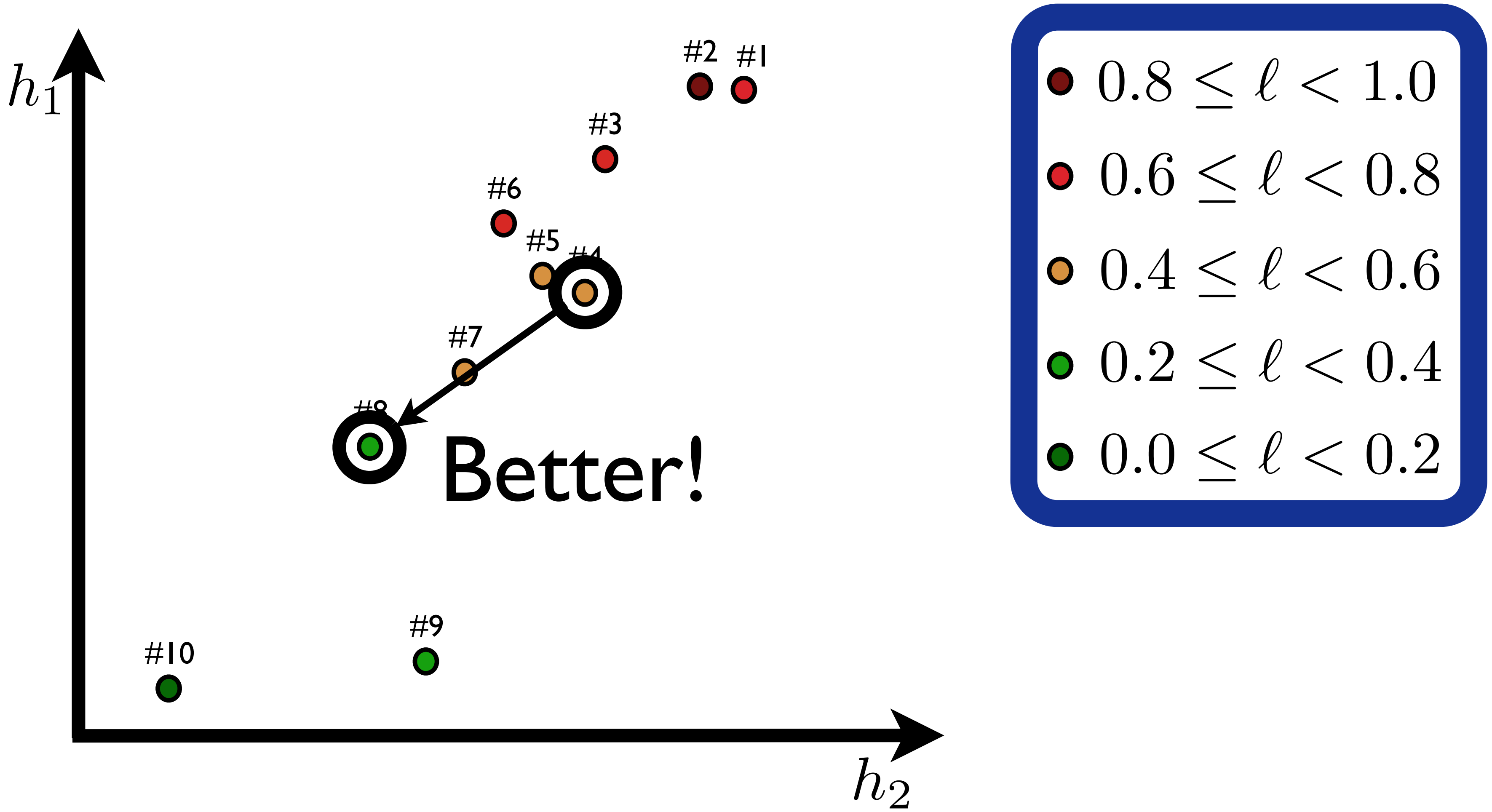
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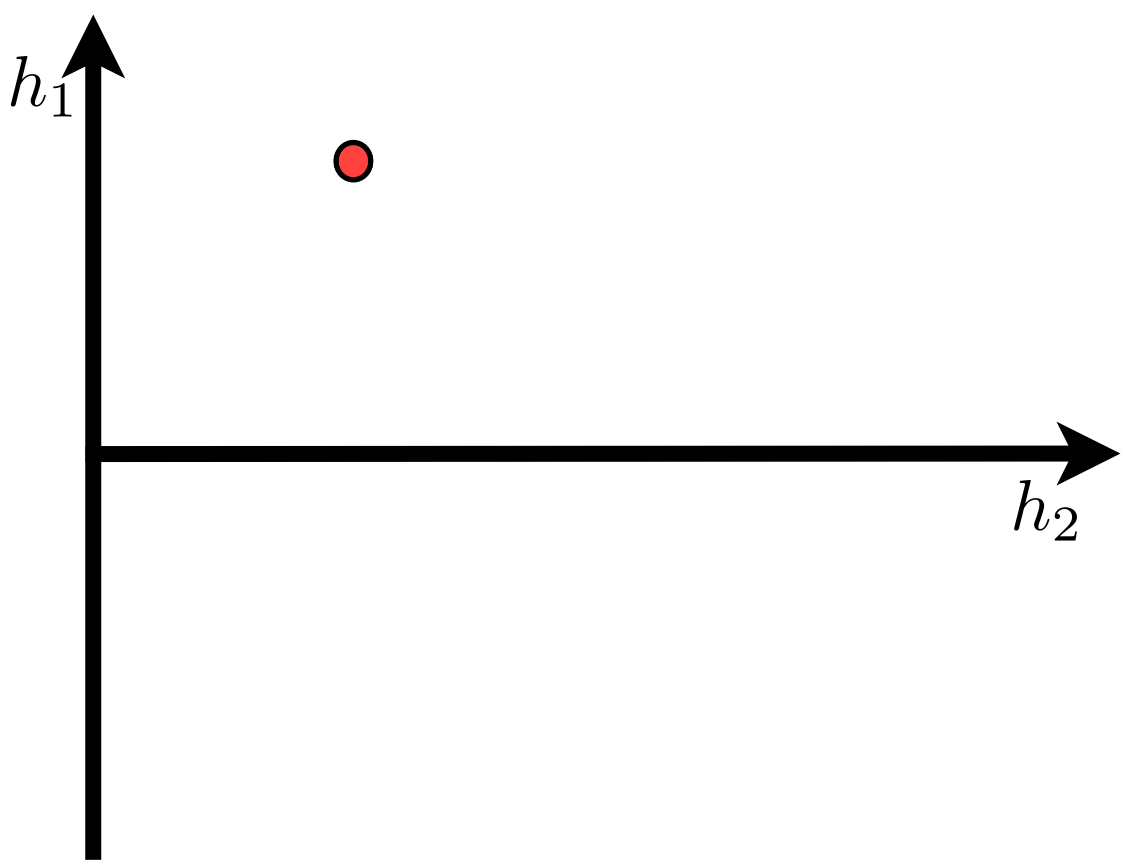
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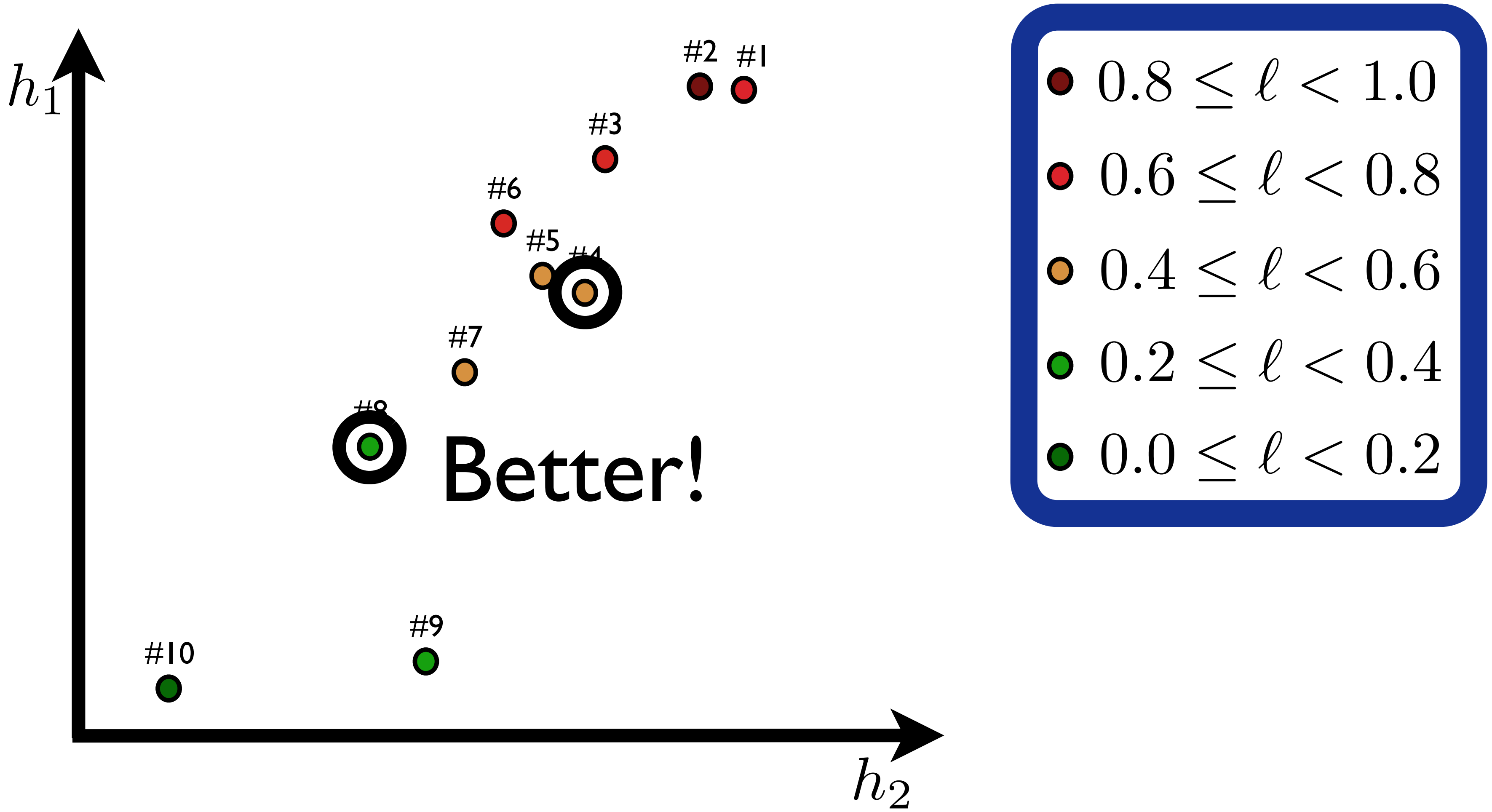

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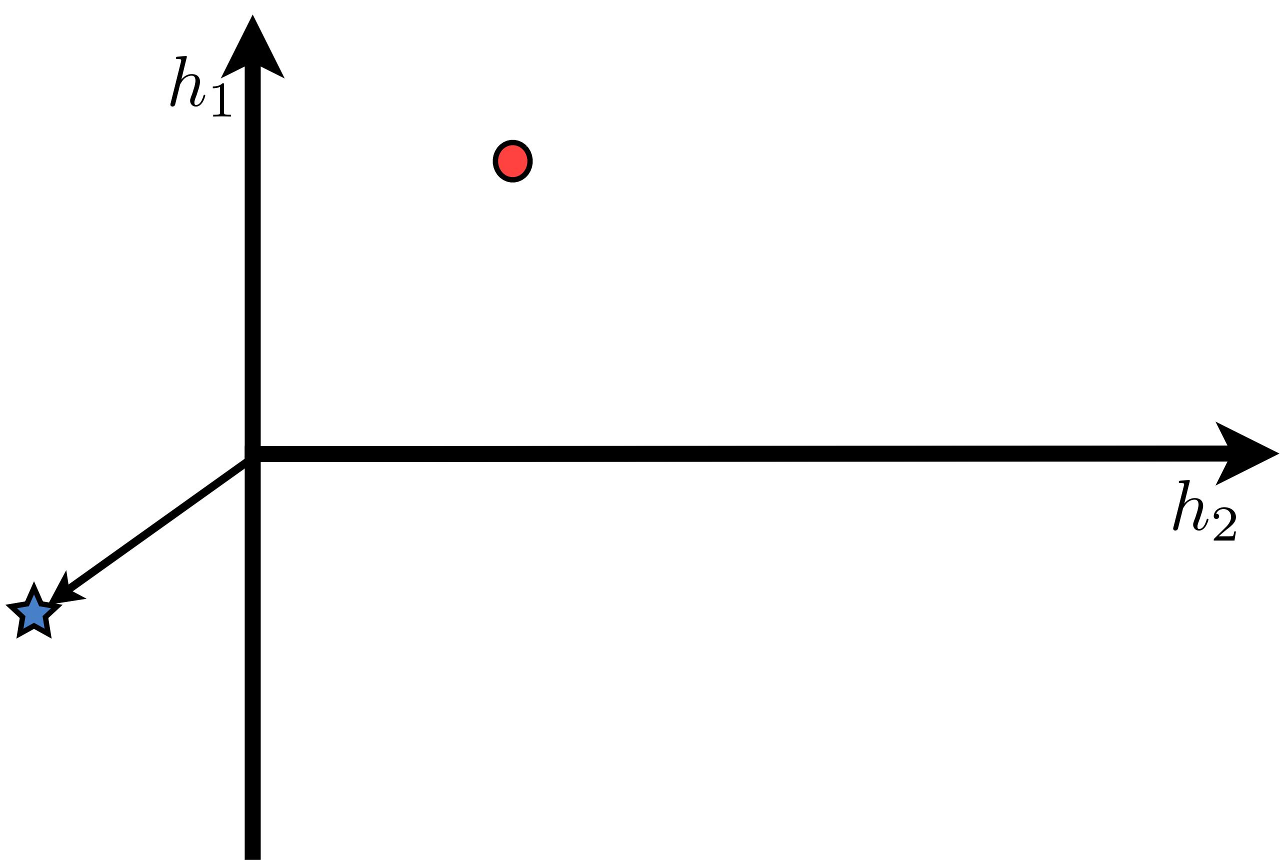

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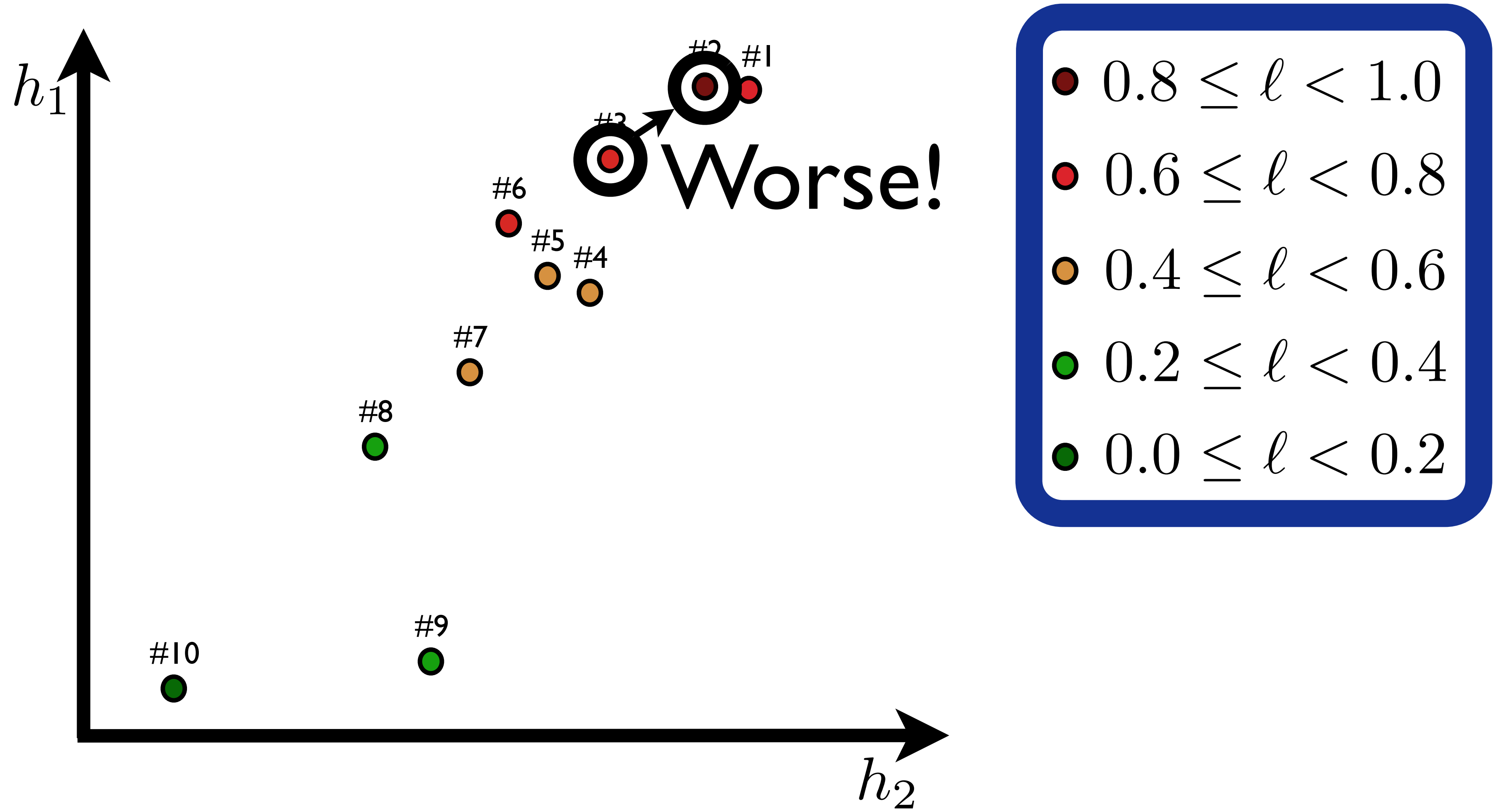

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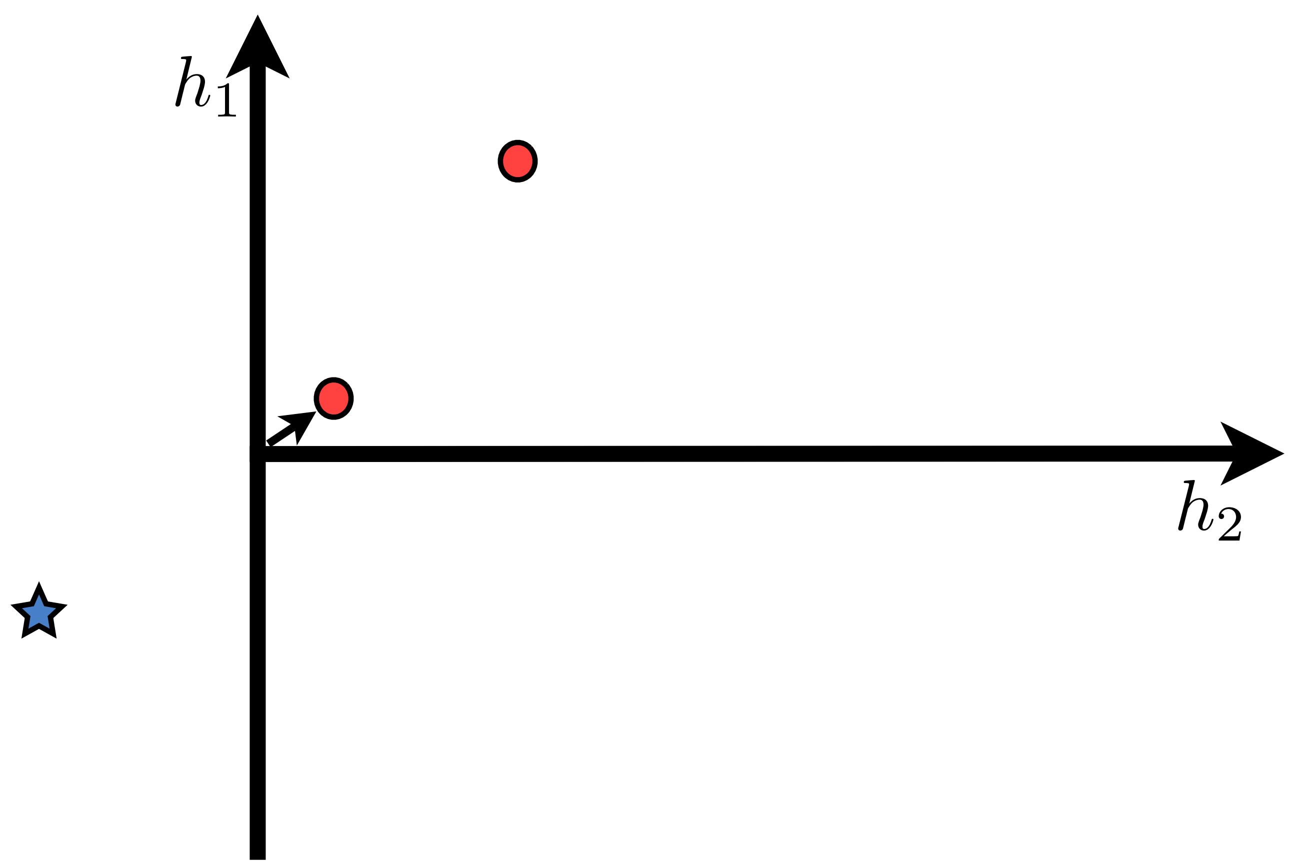

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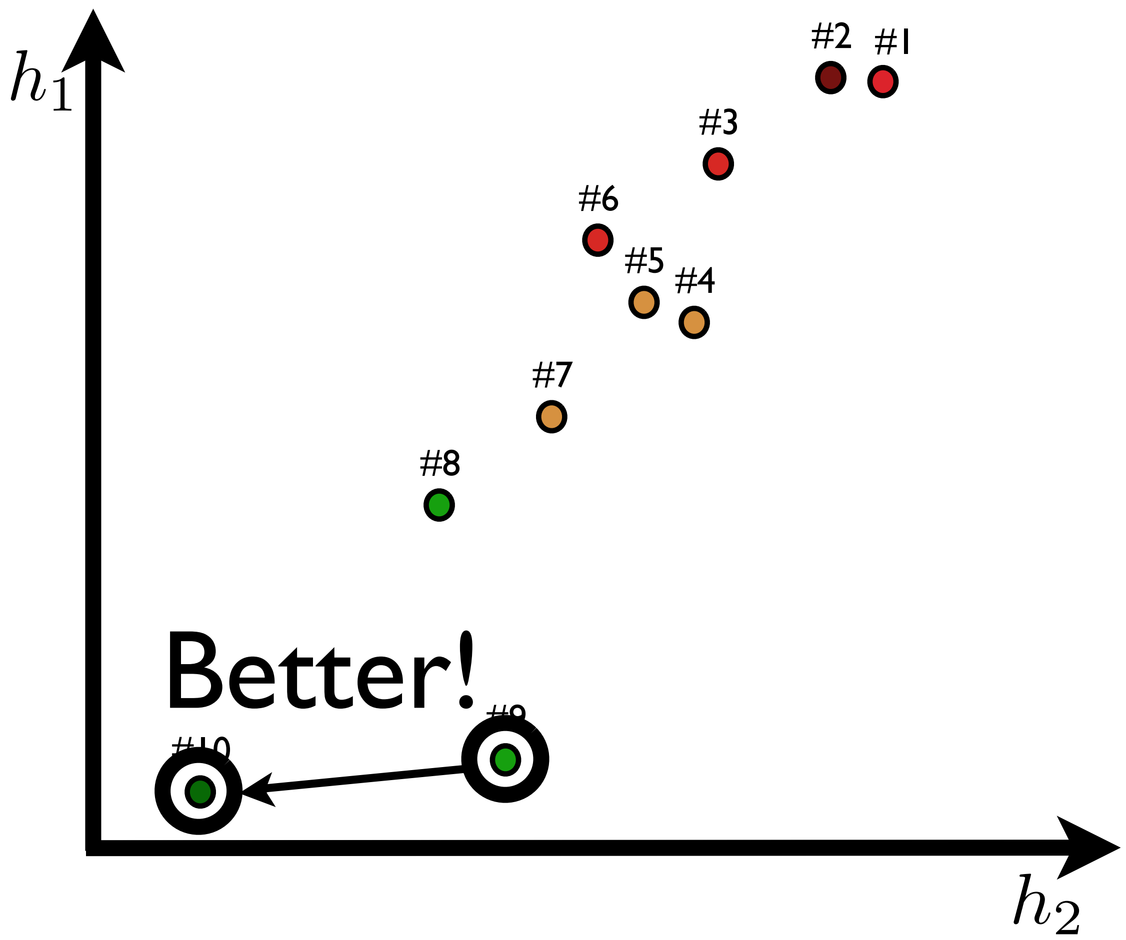

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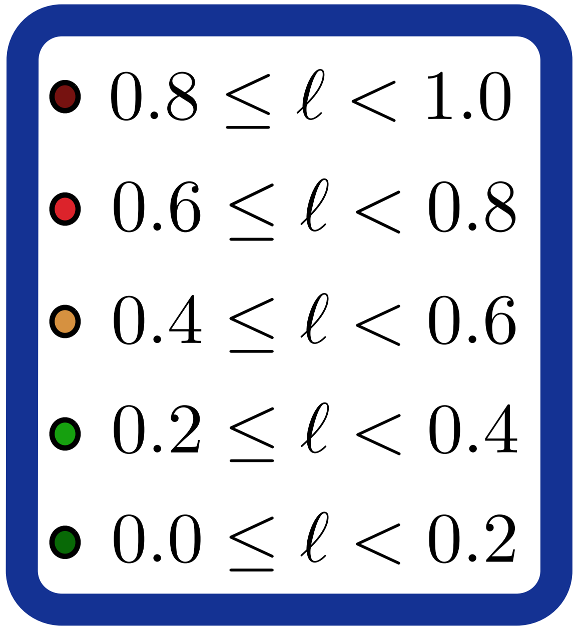

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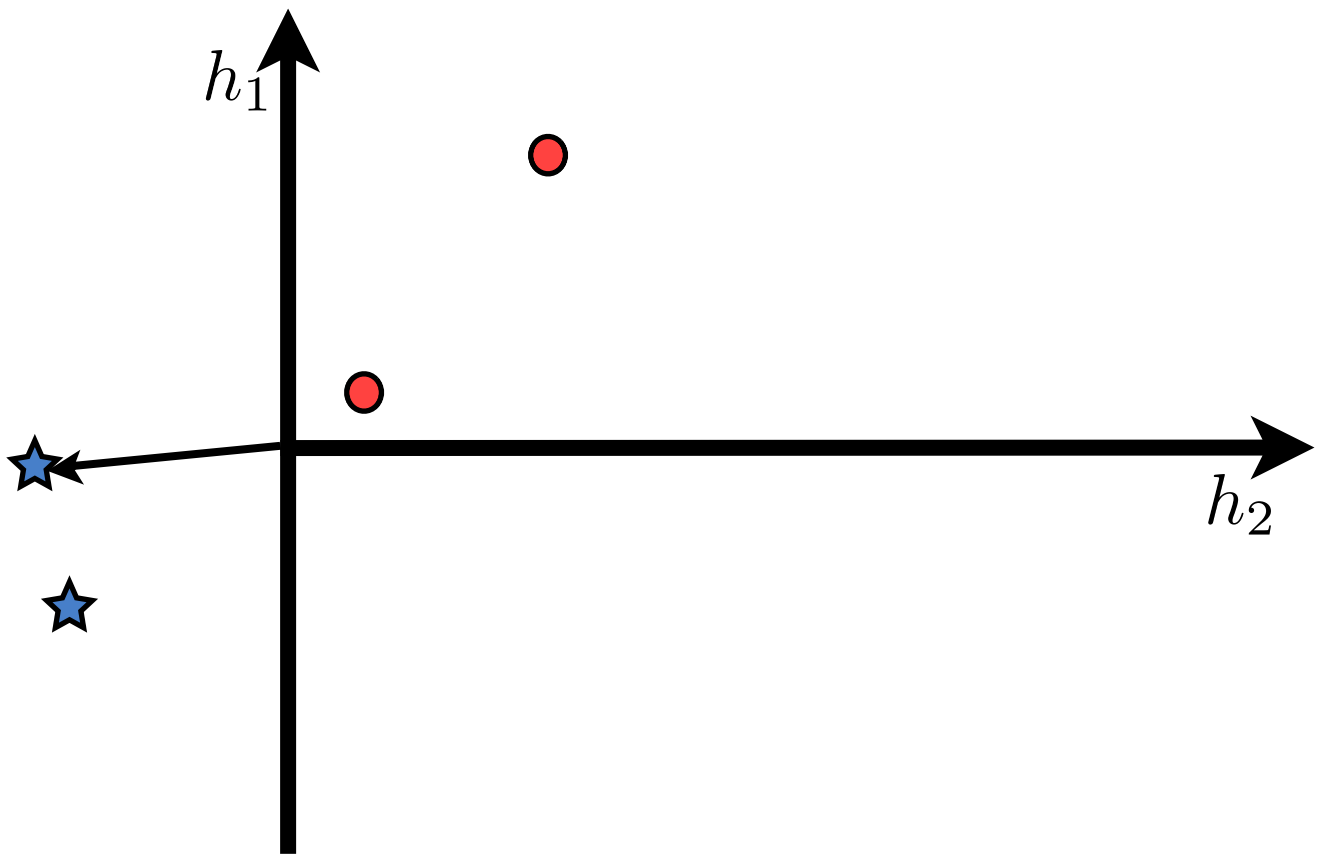

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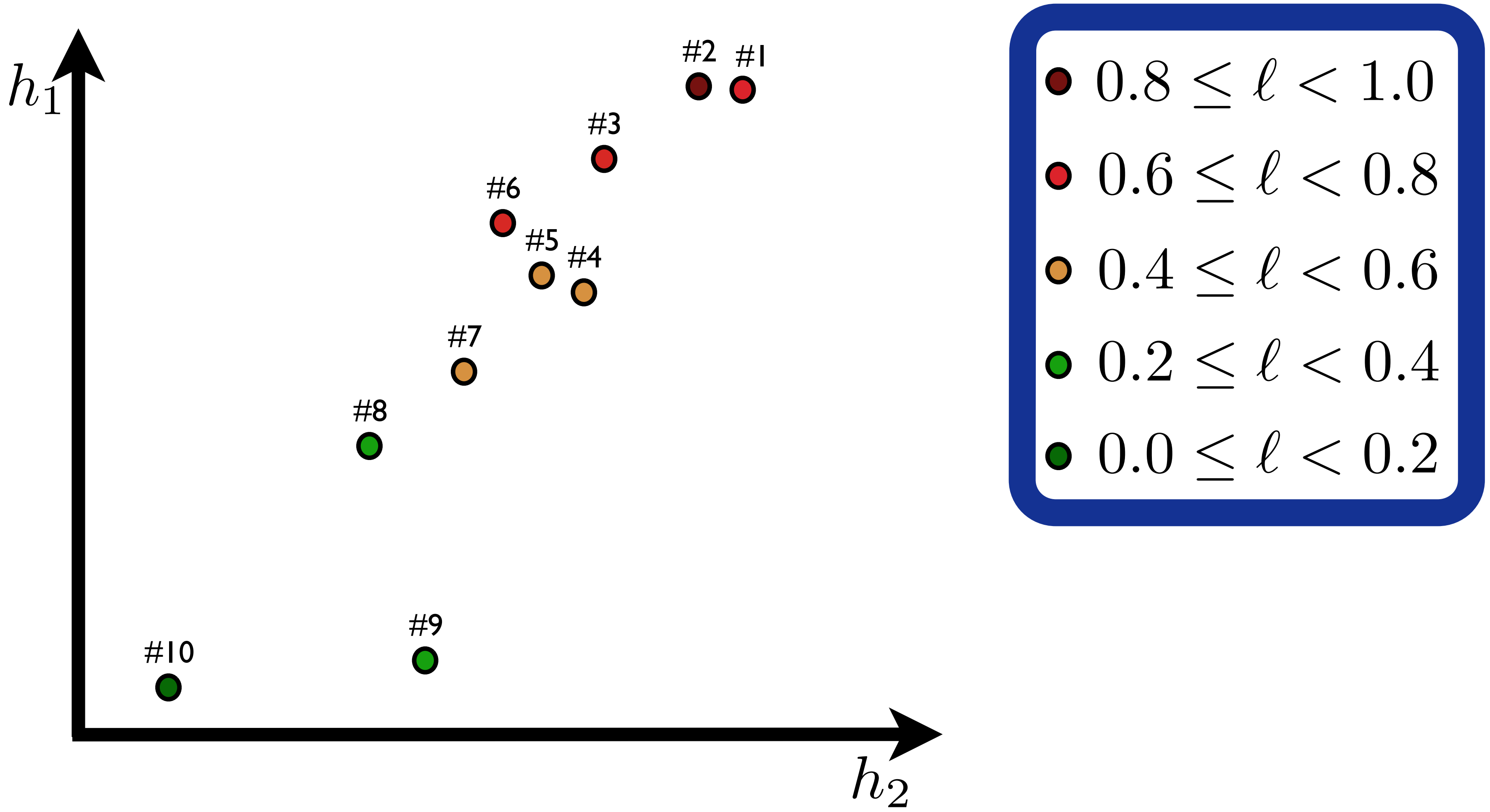

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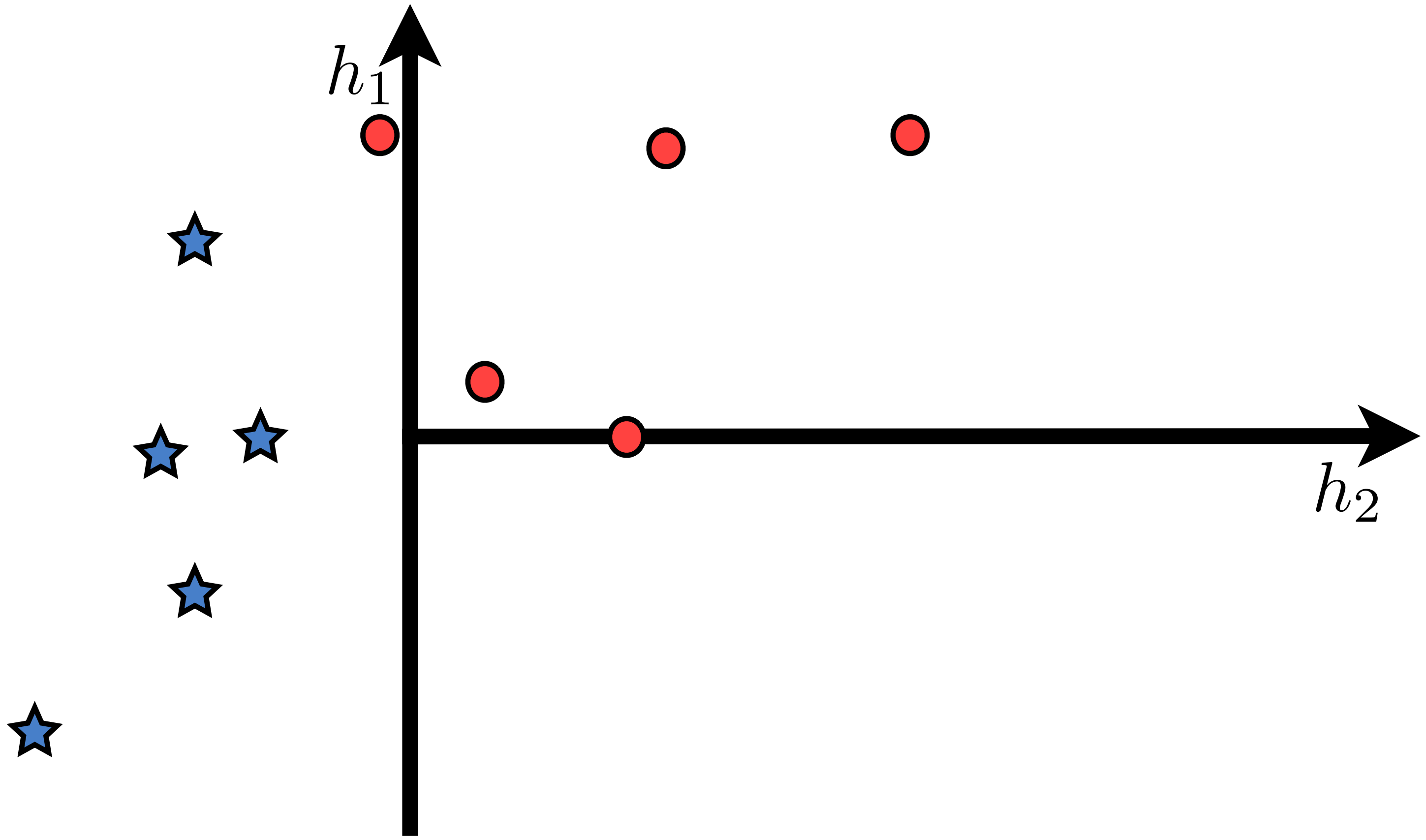
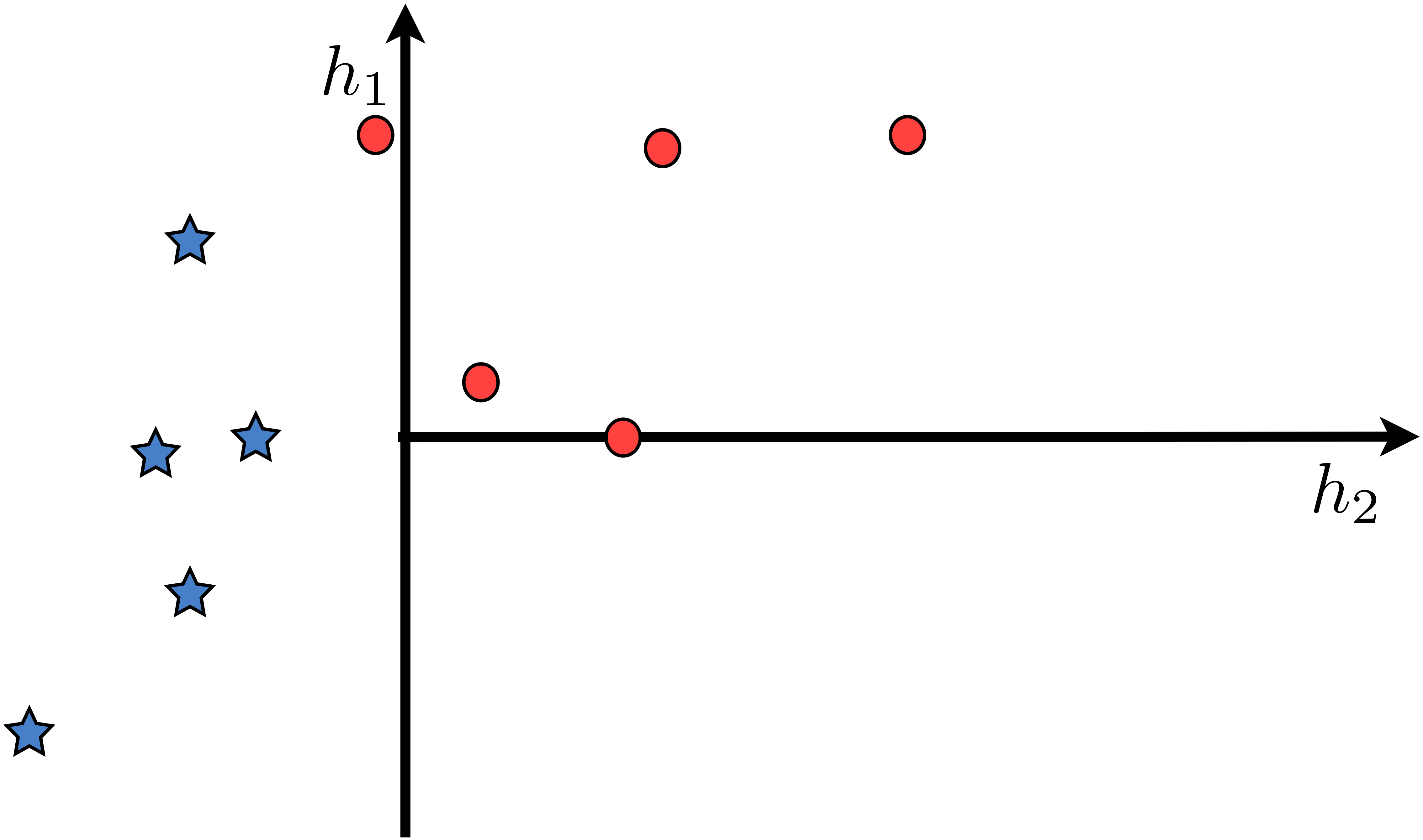
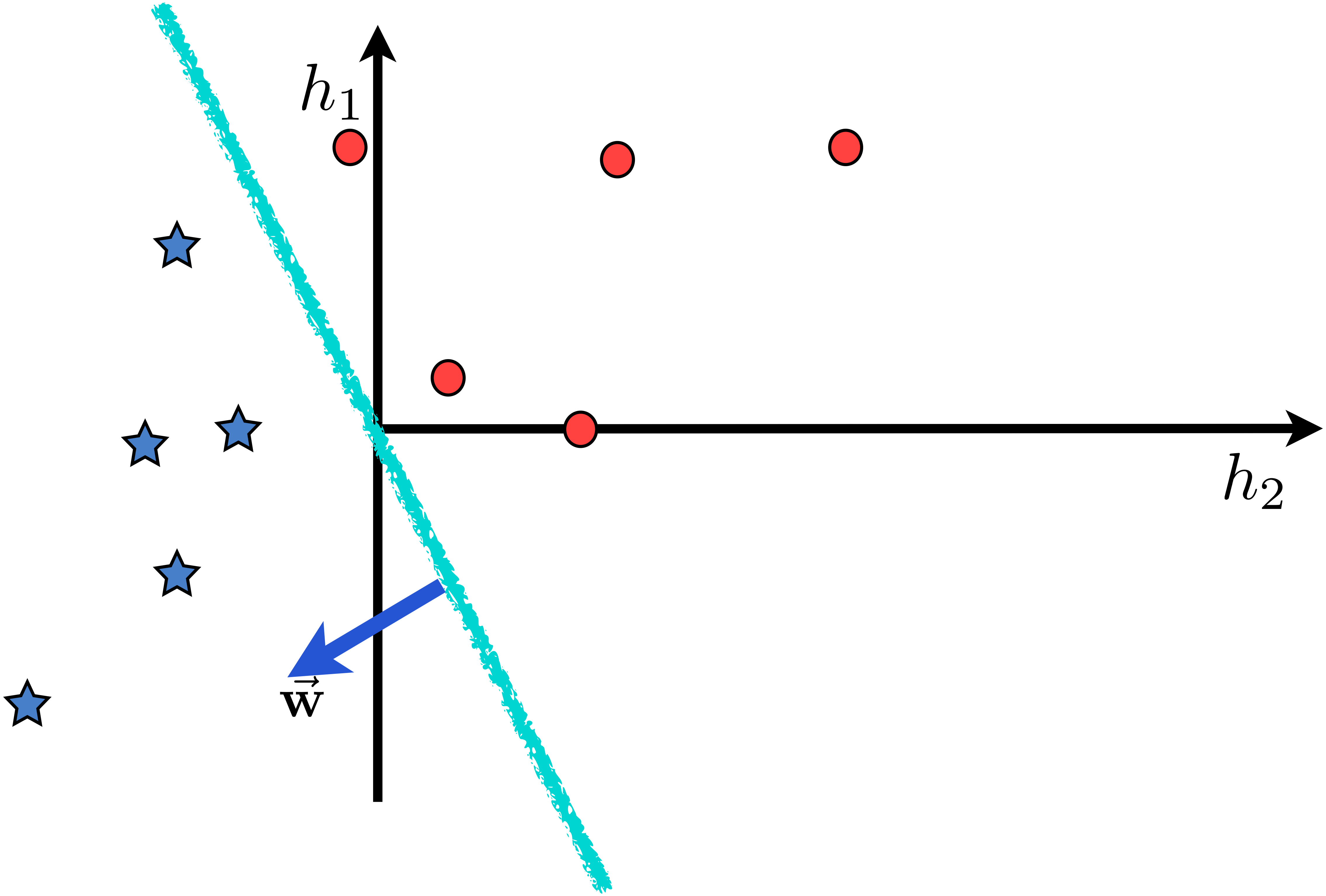


h_1
h_2

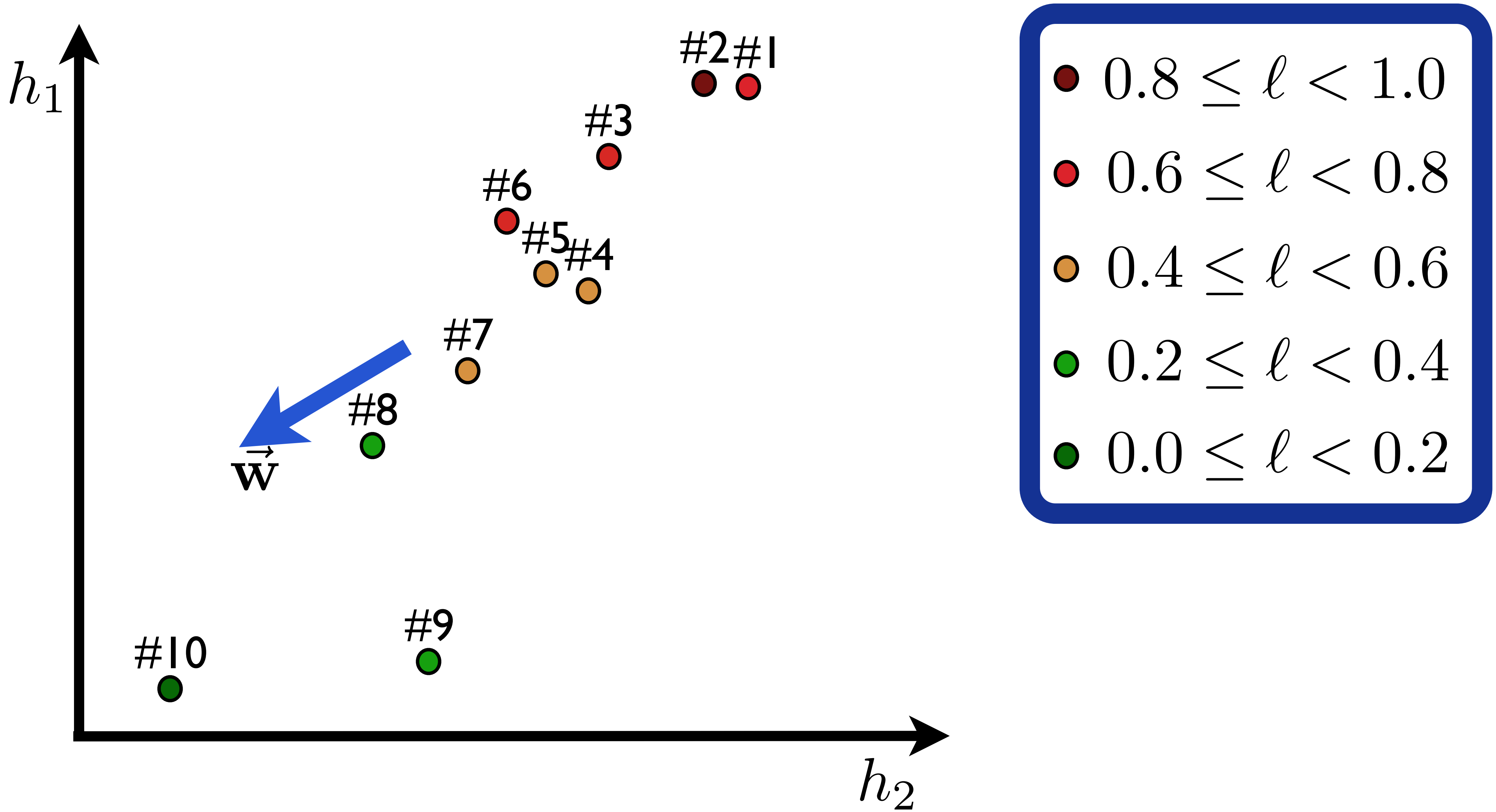


Fit a linear model



Fit a linear model

K-Best List Example

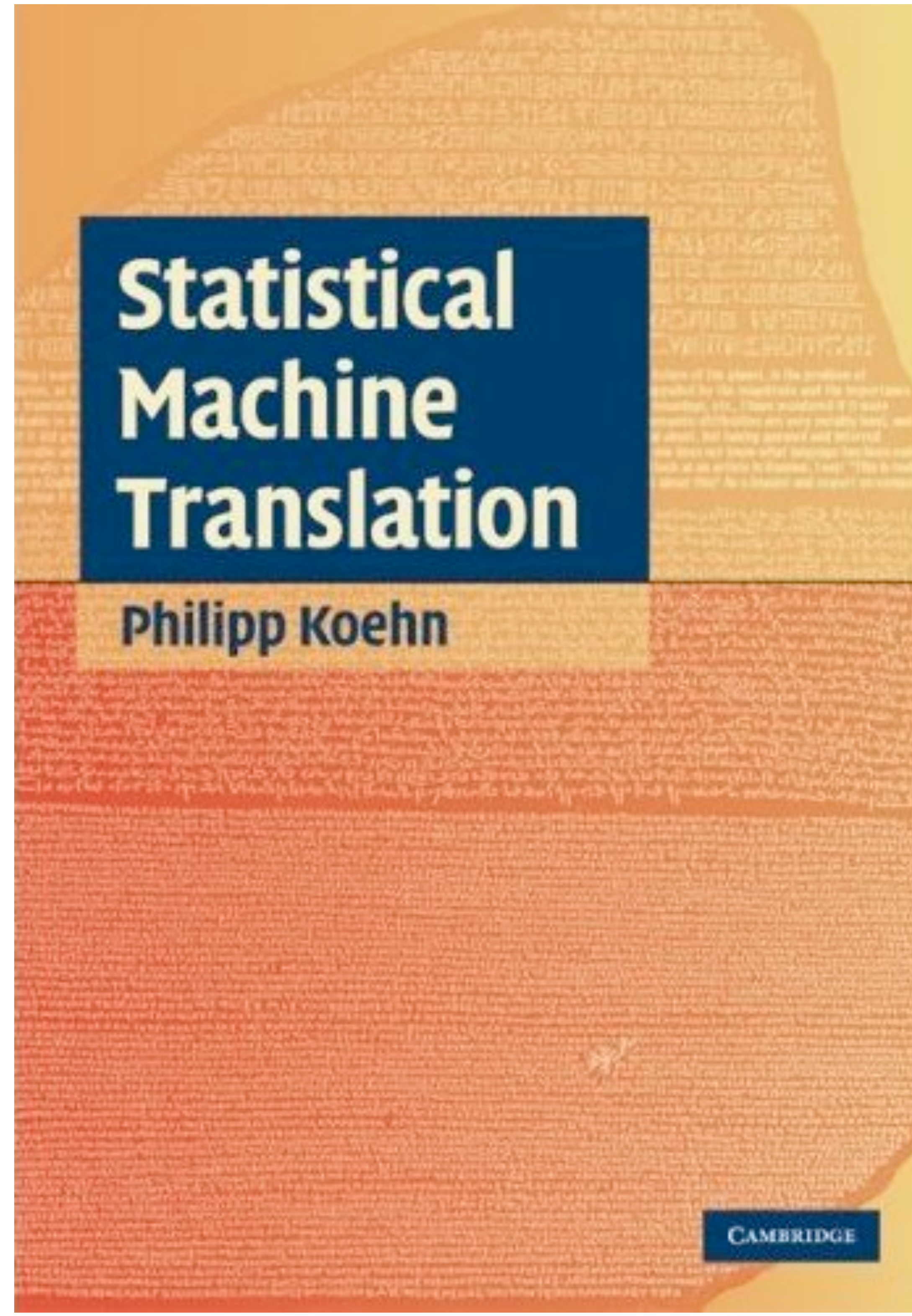


Summary

- Evaluation metrics
  - Figure out how well we're doing
  - Figure out if a feature helps
  - **Train your system**
- What's a great way to improve translation?
  - **Improve evaluation!**

Reading

- Read chapter 9 from the textbook
- HW4 will be a discriminative re-ranking project



Announcements

- HW3 has been released. It is due a week from Thursday.
- Upcoming:
  - Term project (25% of your final grade) and the language research project (10%)
  - These are group projects (2-6 students), where the work scales to the group size
  - Specifications will be posted soon

Term project

- **Problem description** – similar to the descriptions on the HW assignments
- **Data collection** – used to train a model, and evaluate its performance
- **Objective function** – score submissions on a leaderboard
- **Default system** – An implementation of the simplest possible solution
- **Baseline system** – An implementation of a published baseline

Language Research

- Gather monolingual and bilingual data for the language
- Investigate where it is spoken, and what other languages its speakers are exposed to
- Collect information about the syntax and morphology of the language
- Describe its writing system
- Create your own NLP tools for the language (# will vary by team size)