

Sparse Activations as Conformal Predictors

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Conformal prediction (CP)

- **Uncertainty quantification** framework: strong coverage **guarantees**, model-agnostic, and distribution-free.
- Given a **non-conformity score**, CP constructs **prediction sets** for test instances using calibration data.

[Vovk et al., 2005](#); [Angelopoulos and Bates, 2023](#)

Sparse activation functions

- Fenchel-Young losses: framework for sparse activations interpretable as set prediction, such as:
- γ -entmax family: softmax ($\gamma=1$) and sparsemax ($\gamma=2$); sparse for $\gamma > 1$; temperature-controlled sparsity

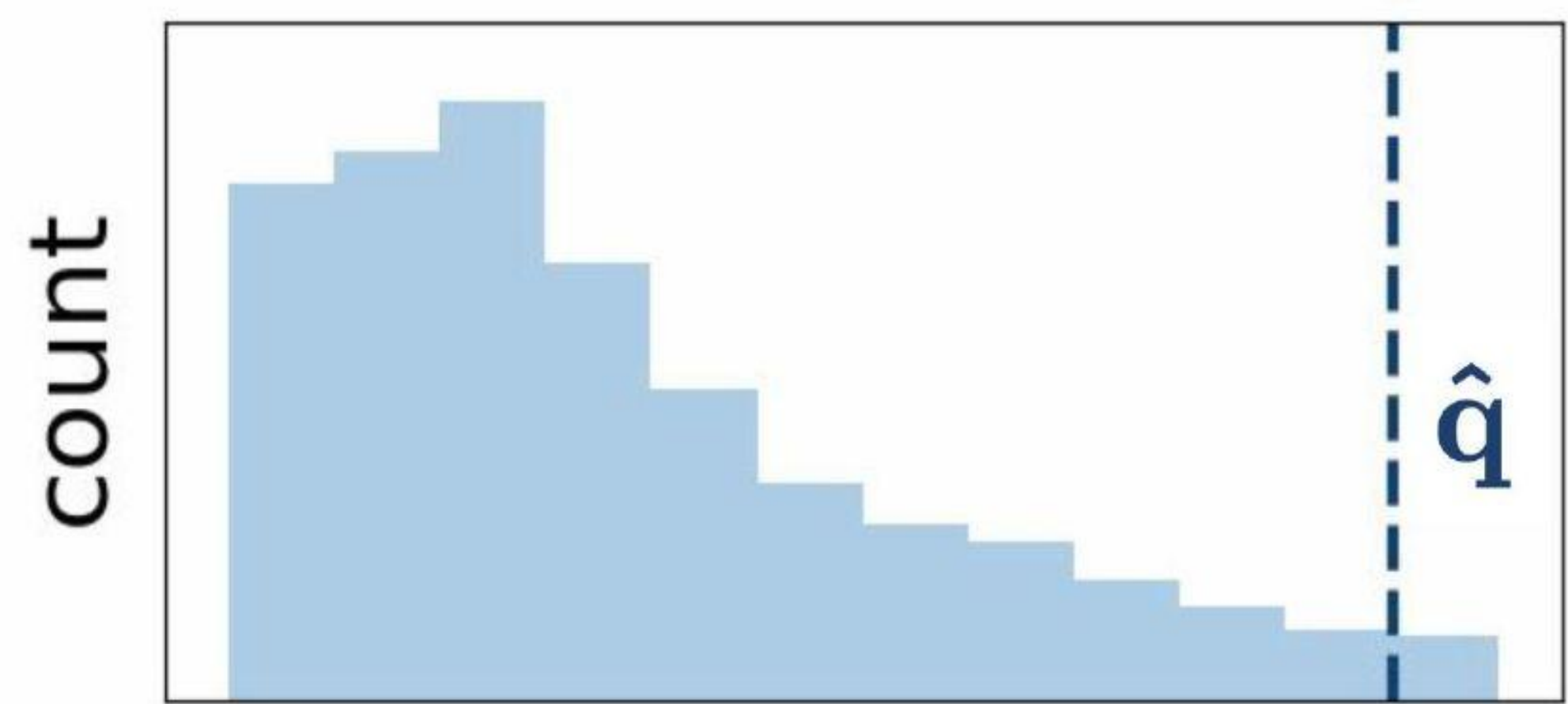
[Martins and Astudillo, 2016](#); [Peters et al., 2019](#); [Blondel et al., 2020](#)

new
conformal
predictor

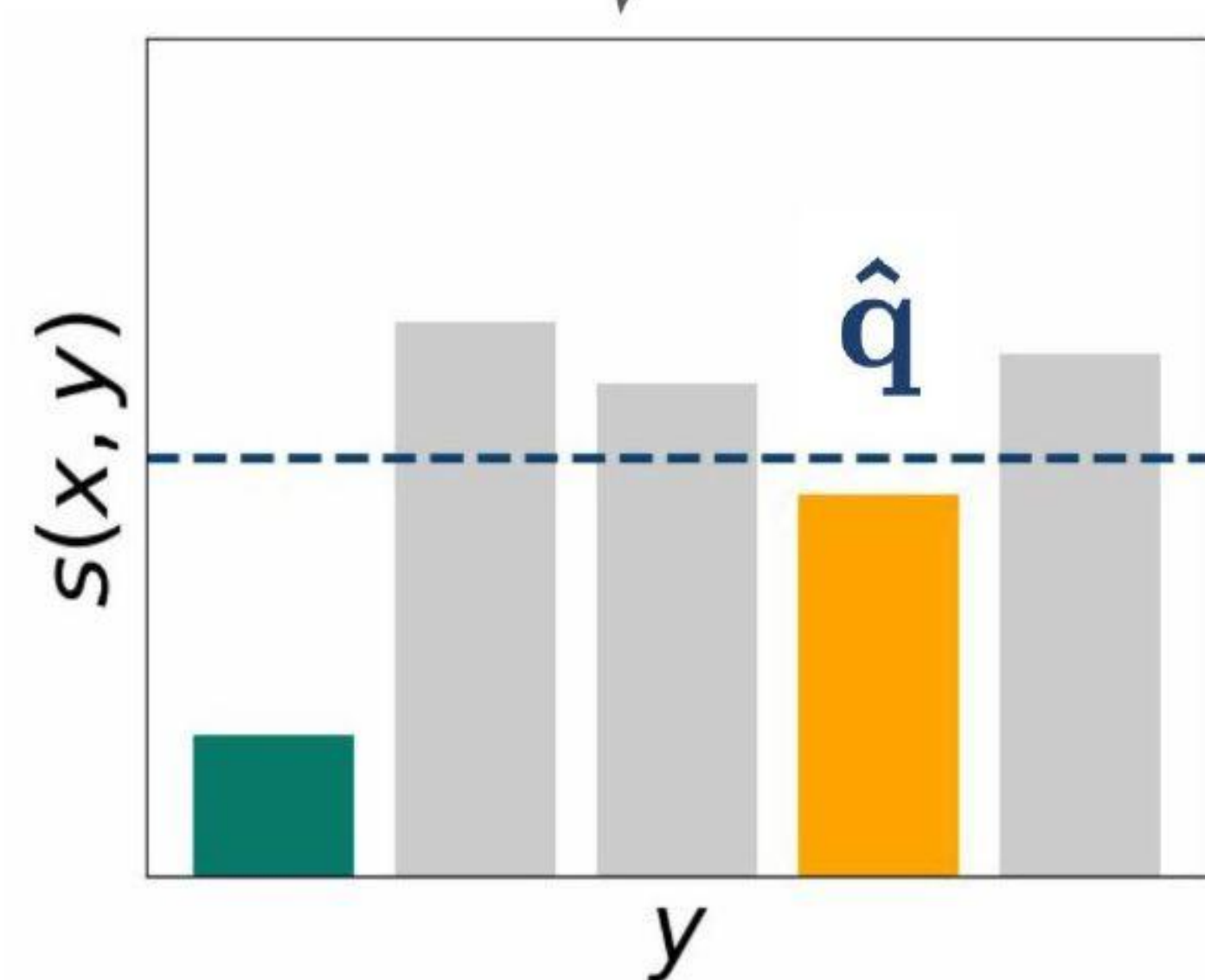


temperature
scaling of
sparsemax

generalization
to the
 γ -entmax
family



$$s(x, y) = \|\mathbf{z}_{1:k(y)} - z_{k(y)}\mathbf{1}\|_{\frac{1}{\gamma-1}}$$



Conformal Prediction

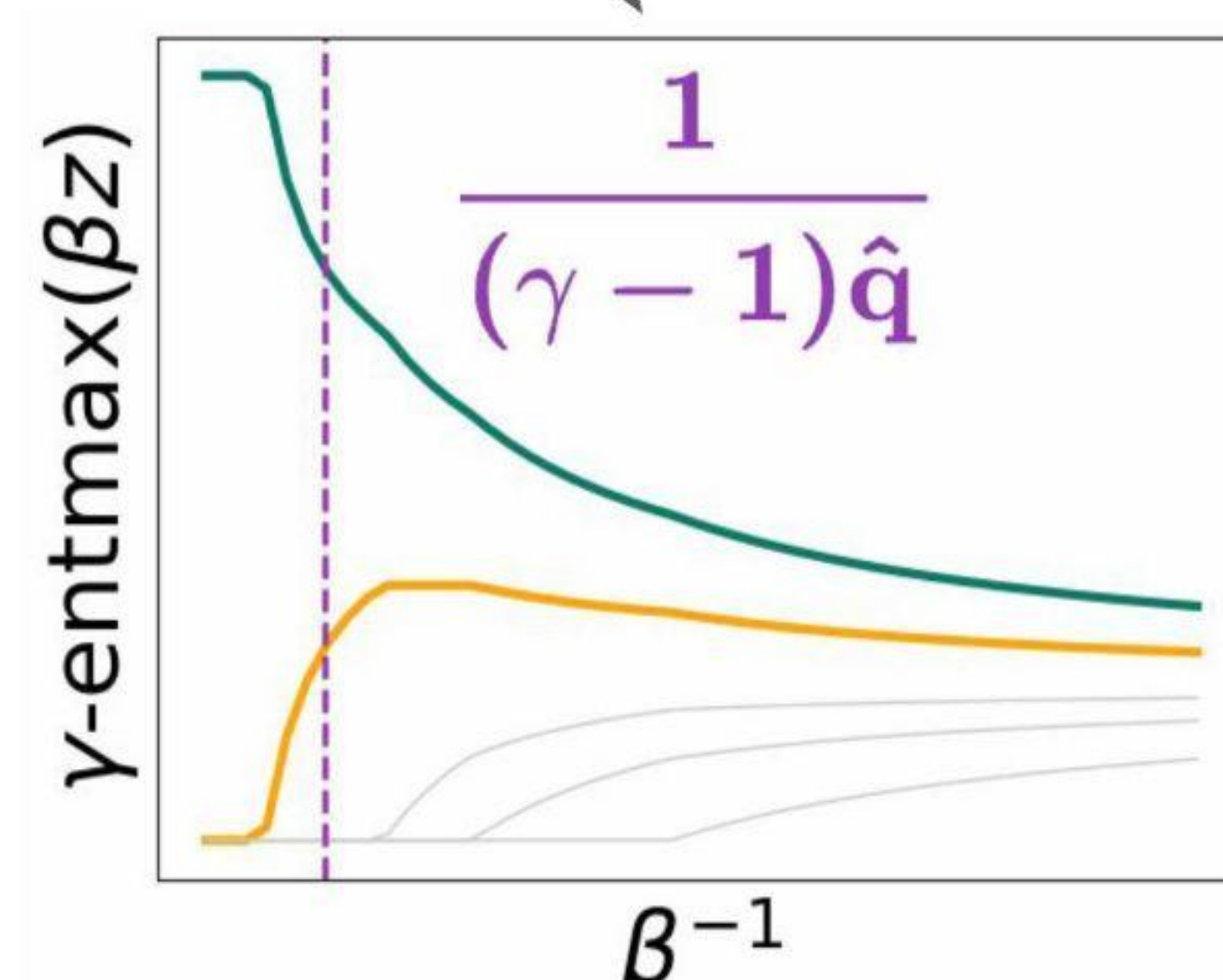
Calibration

$$\frac{\lceil (n+1)(1-\alpha) \rceil}{n}$$

quantile

expanded family of
non-conformity
scores

empirical
validation on
different tasks



Temperature Scaling

See it live!



tinyurl.com/sparseconformal

Conformalizing entmax

Let $z_1 > \dots > z_K$, support is $j \in S(\beta\mathbf{z}; \gamma) \iff \sum_{k=1}^{j-1} [(\gamma-1)\beta(z_k - z_j)]^{\frac{1}{\gamma-1}} < 1$

Building a conformal predictor, $C_\alpha: \mathcal{X} \rightarrow 2^{\mathcal{Y}}$, with score:

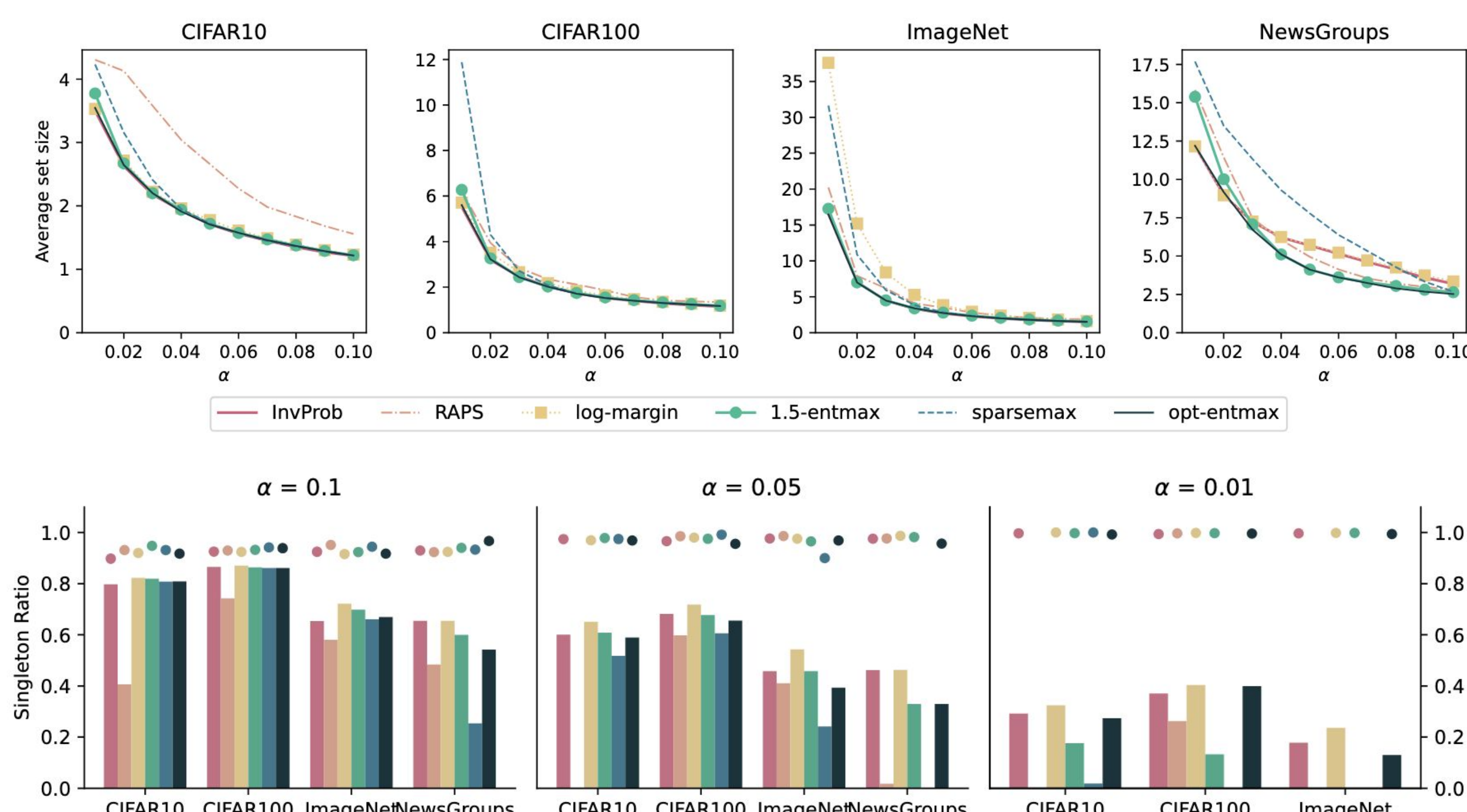
$$s(x, y) = \|\mathbf{z}_{1:k(y)} - z_{k(y)}\mathbf{1}\|_\delta, \text{ yields: } C_\alpha(x) = S(\beta\mathbf{z}; \gamma)$$

Interesting findings

- γ can be tuned, yielding method **opt-entmax**
- limit case (softmax) \rightarrow log-odds ratio (**log-margin**):

$$s(x, y) = \|\mathbf{z}_{1:k(y)} - z_{k(y)}\mathbf{1}\|_\infty = z_1 - z_{k(y)} = \log \frac{p_1}{p_{k(y)}}$$

Results



- choice of score is crucial and **task-dependent**
- new methods (**log-margin** and **opt-entmax**):
- **efficiency** ✓
- **adaptiveness** ✓
- **Interpretability** ✓
- **natural calibration assessment**

