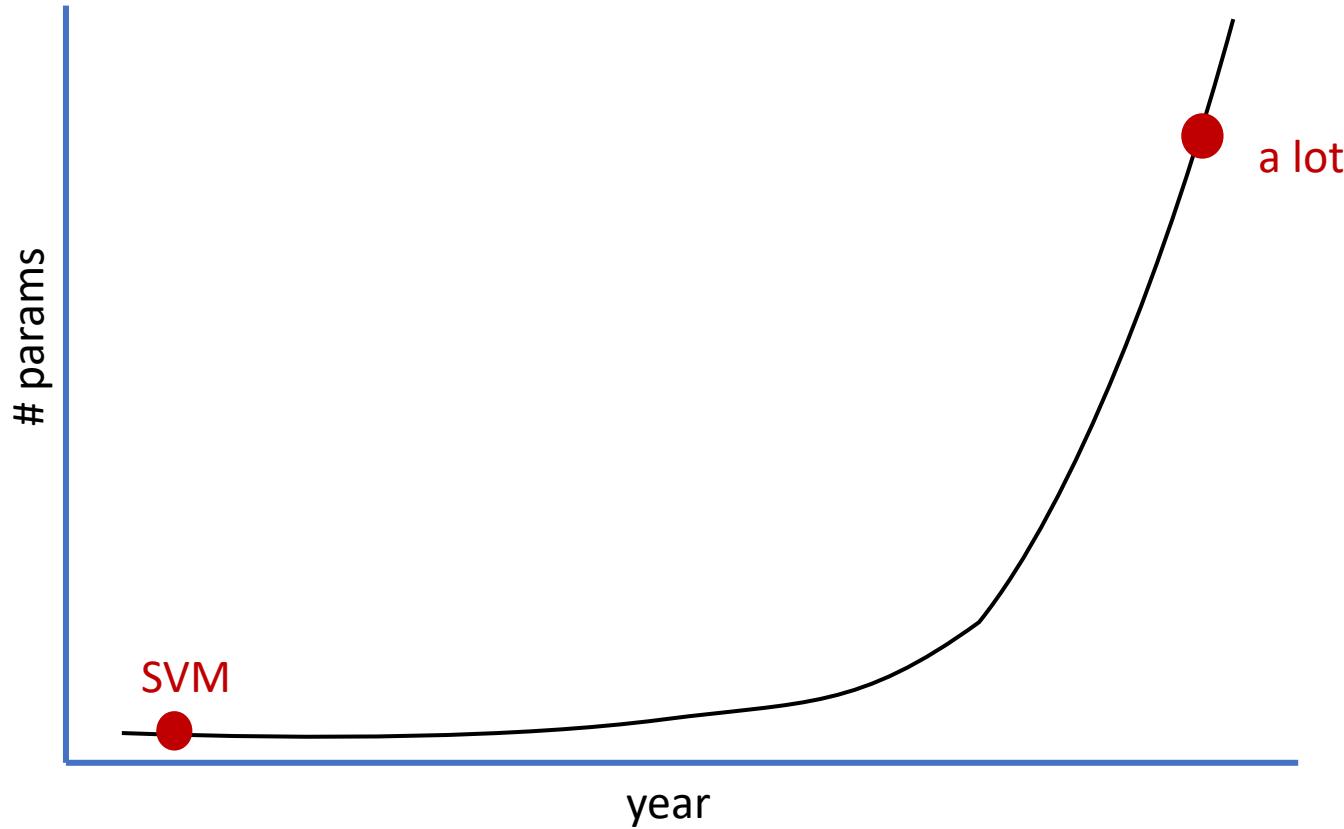


Consistent Accelerated Inference via Confident Adaptive Transformers



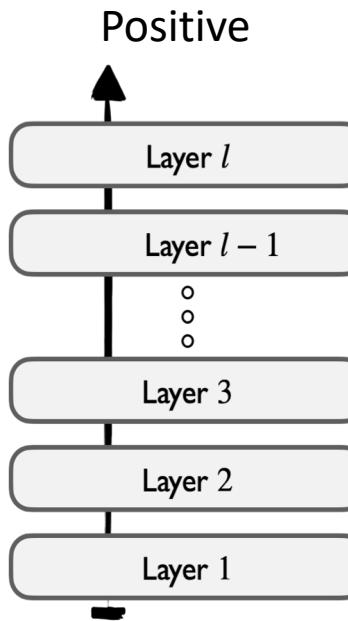
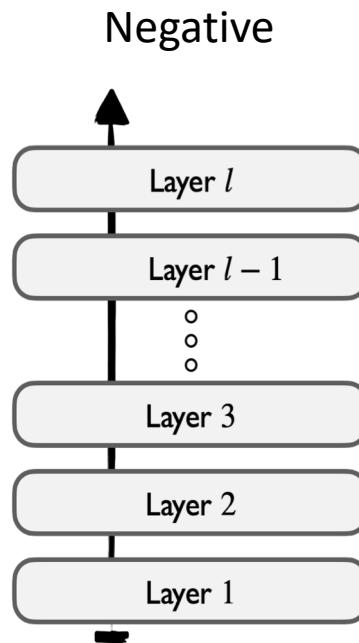
Tal Schuster*, Adam Fisch*, Tommi Jaakkola, Regina Barzilay

Number of parameters in NLP models



Is the full capacity always needed?

Movie review sentiment analysis:



Can we use
fewer layers?

“Everything of any interest was thoroughly covered in the original film, but like many people who have nothing to say, *Part II* won't shut up.”

“This movie is fantastic!”

Confident Adaptive Transformers

Classifier F on top of the last layer l :

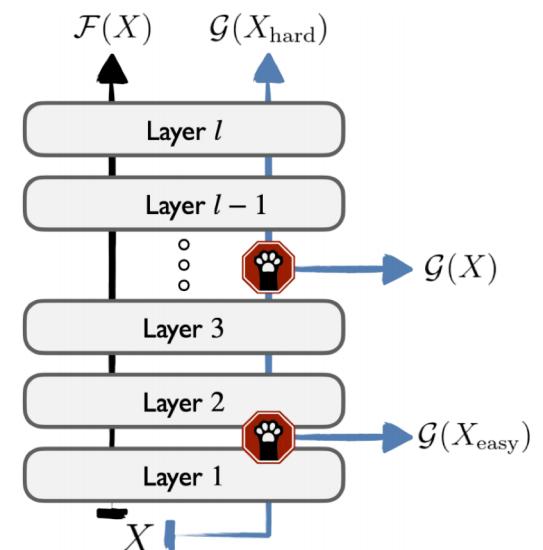
$$F(x) := H_l(T_l(T_{l-1}(\dots(T_1(x))))$$

Earlier classifiers:

$$F_1(x) := H_1(T_1(x))$$

$$F_2(x) := H_2(T_2(T_1(x)))$$

$$F_k(x) := H_k(T_k(\dots(T_1(x)))) , k < l$$



Create an amortized model $G(x)$ that can choose from F_1, \dots, F_l

Our goal

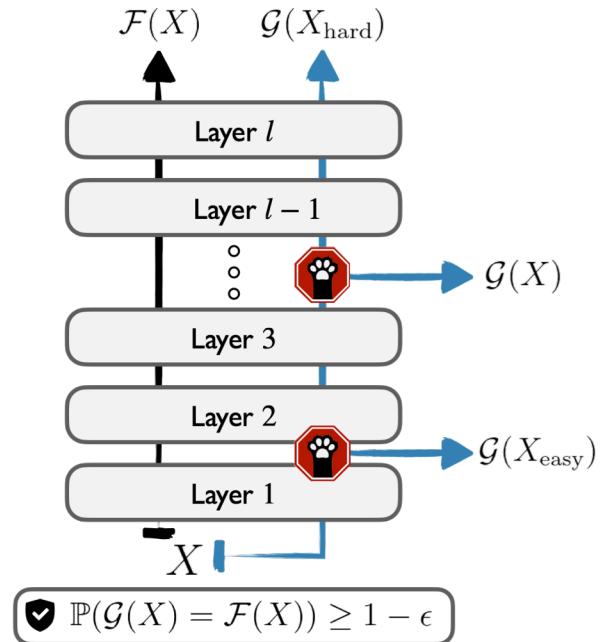
Reduce computational effort (fewer layers when possible)
while guaranteeing consistency with original classifier:

$$\mathbb{P}(\mathcal{G}(X_{n+1}) = \mathcal{F}(X_{n+1})) \geq 1 - \epsilon$$

Challenges

How to measure confidence?

When can we exit?

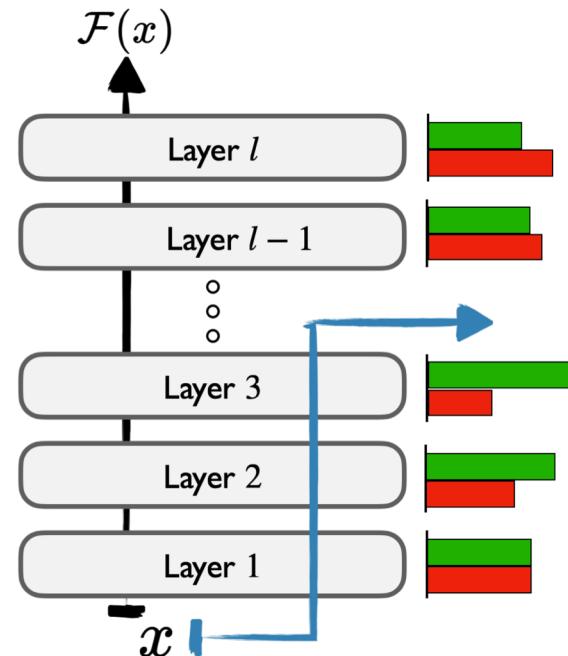


How to measure confidence?

Previous models rely on intrinsic measures

- Softmax response (Huang et al., 2018; Schwartz et al. 2020; Xin et al., 2020)
- Entropy (Liu et al., 2020; Geng et al., 2021)
- Patience (Zhou et al., 2020)

- Doesn't directly measure consistency
- Doesn't support non-classification tasks



Meta early exit classifier

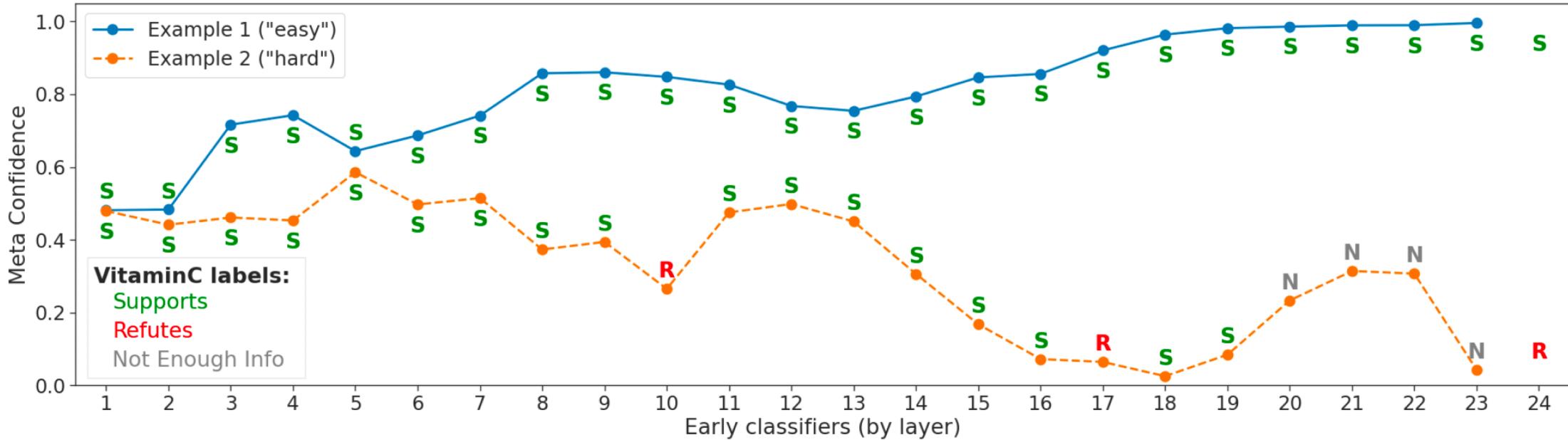
Directly **estimates the consistency**

A binary MLP $M_k(x)$ that predicts $\mathbf{1}\{F_k(x) = F(x)\}$

Input to M_k :

- Early predictor hidden state: $\phi\left(W_p^{(k)} h_{[CLS]}^{(k)}\right)$
- Meta features:
 - Current prediction
 - History of predictions
 - Probability of current prediction
 - Difference in probability of top two predictions

Meta early exit classifier



(Ex.1) Claim: All airports in Guyana were closed for all international passenger flights until 1 May 2020.

Evidence: Airports in Guyana are closed to all international passenger flights until 1 May 2020.

(Ex.2) Claim: Deng Chao broke sales record for a romantic drama.

Evidence: The film was a success and broke box office sales record for mainland-produced romance films.

When can we exit?

Previous models use arbitrary thresholds

We are interested in a **marginal consistency guarantee**

$$\mathbb{P}(\mathcal{G}(X_{n+1}) = \mathcal{F}(X_{n+1})) \geq 1 - \epsilon$$

$$\mathcal{G}(x; \tau) := \begin{cases} \mathcal{F}_1(x) & \text{if } \mathcal{M}_1(x) > \tau_1, \\ \mathcal{F}_2(x) & \text{else if } \mathcal{M}_2(x) > \tau_2, \\ \vdots & \\ \mathcal{F}_l(x) & \text{otherwise,} \end{cases}$$

$\tau = (\tau_1, \dots, \tau_{l-1})$ are confidence thresholds

When can we exit?

Pick one of the layers that are **consistent** with F

$$T(x) := \{i : F_i(x) = F(x)\}, \quad i \in [1, l - 1]$$

Conformal prediction

V. Vovk, A. Gammerman, and G. Shafer (2005)

Given n calibration examples $(X_i, Y_i) \in \mathcal{X} \times \mathcal{Y}$ and a desired tolerance level ϵ , for a new input X_{n+1} :

return a **set of predictions** $C_{n,\epsilon}(X_{n+1})$, such that

$$\mathbb{P}\left(Y_{n+1} \in C_{n,\epsilon}(X_{n+1})\right) \geq 1 - \epsilon$$

Meaning, $C_{n,\epsilon}$ contains the correct answer at least $1 - \epsilon$ of the time

Regular conformal sets don't work

Example:

$$T(x) = \{3, 5, \dots, l - 1\}$$

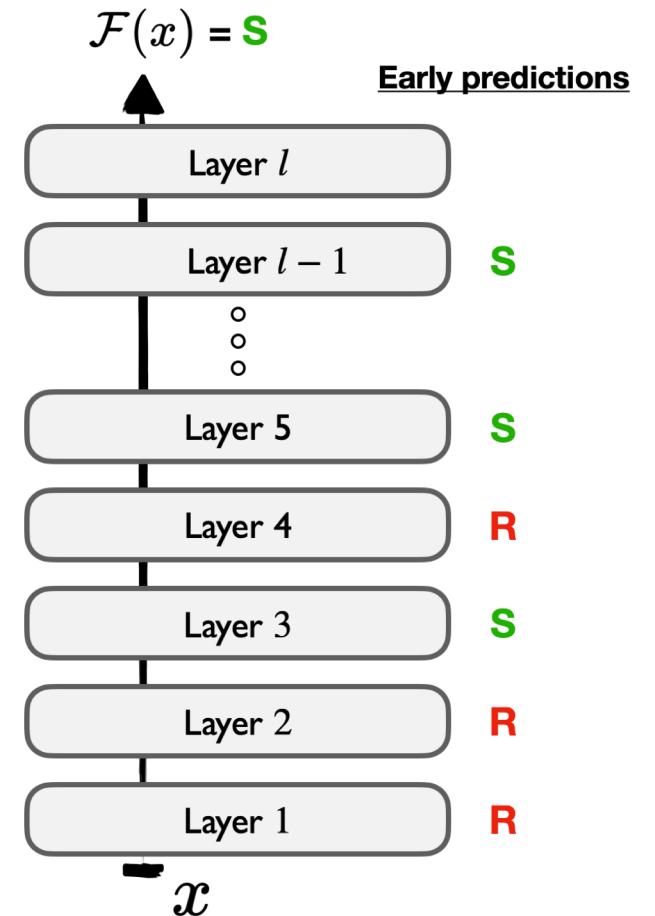
Valid prediction set (contains the right answer):

$$C_{n,\epsilon}(x) = \{2, 3, 4, l - 1\}$$

can lead to false predictions

Instead, we predict the **inconsistent** layers
and avoid them

$$I(x) := \{i : i \notin T(x)\}, \quad i \in [1, l - 1]$$



Conformalized early exits

We look at the **inconsistent** layers:

$$I(x) := \{i : F_i(x) \neq F(x)\}, \quad i \in [1, l - 1]$$

G is **ϵ -consistent** if it **avoids** any $I(x)$ layers more than ϵ -fraction of the time

We obtain a conservative prediction C_ϵ :

$$\mathbb{P}(I(X) \subseteq C_\epsilon(X)) \geq 1 - \epsilon$$

For $K := \min\{j : j \in \overline{C}_\epsilon(X)\}$, we have: $\mathbb{P}(F_K(X) = F(X)) \geq 1 - \epsilon$

 Complement

Independent calibration

For each layer, compute the empirical distribution of inconsistent scores:

$$v_k^{(1:n,\infty)} = \{M_k(x_i) : x_i \in D_{\text{cal}}, F_k(x_i) \neq F(x_i)\} \cup \{\infty\}$$

And set the threshold by its quantile:

$$\tau_k^{\text{ind}} = \text{Quantile}\left(1 - \alpha_k, v_k^{(1:n,\infty)}\right)$$

Let $\alpha_k = \omega_k \cdot \epsilon$, where $\sum_{k=1}^{l-1} \omega_k = 1$, then $C_\epsilon^{\text{ind}}(X) = \{k : M_k(x) \leq \tau_k^{\text{ind}}\}$ is valid

- In practice, we use uniform Bonferroni correction: $\omega_k = 1/(l-1)$

Limitation: Becomes very conservative as l grows

Shared calibration

Calibrating for the worst-case across inconsistent layers:

$$m^{(1:n,\infty)} = \{M_{\max}(x_i) : x_i \in D_{\text{cal}}, \exists k \text{ s.t. } F_k(x_i) \neq F(x_i)\} \cup \{\infty\}$$

Where $M_{\max}(x) = \max_{k \in [l-1]} \{M_k(x) : F_k(x) \neq F(x)\}$

Again, use quantile:

$$\tau^{\text{share}} = \text{Quantile}\left(1 - \epsilon, m^{(1:n,\infty)}\right)$$

$C_{\epsilon}^{\text{share}}(x) = \{k : M_k(x) \leq \tau^{\text{share}}\}$ is valid

Evaluation

Baselines

- **Static:** Fixed number of layers for any input (tuned on calibration set)
- **Threshold:** Simply exit when the confidence score is over $1 - \epsilon$

Confidence scores:

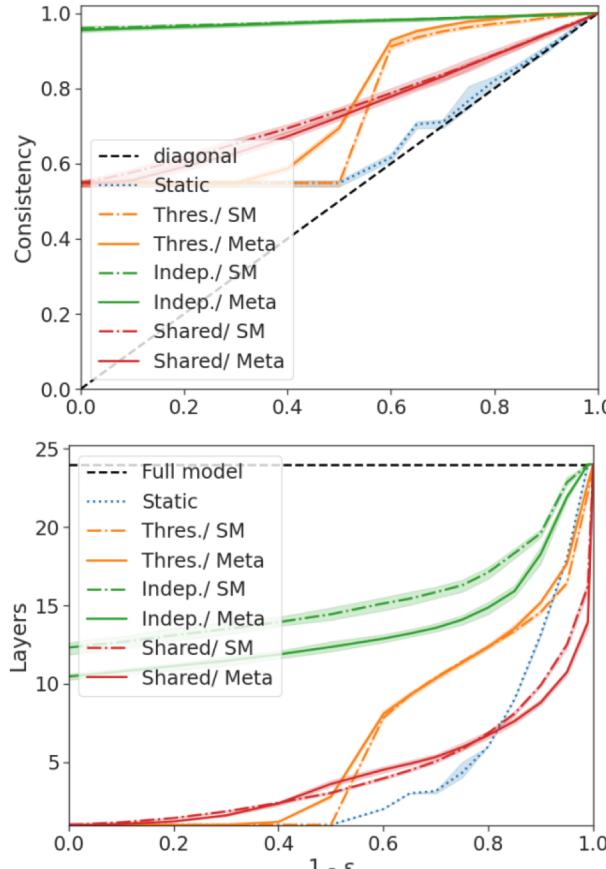
- **SM:** Softmax value (only classification)
- **Meta:** Our meta early exit score

No marginal guarantees

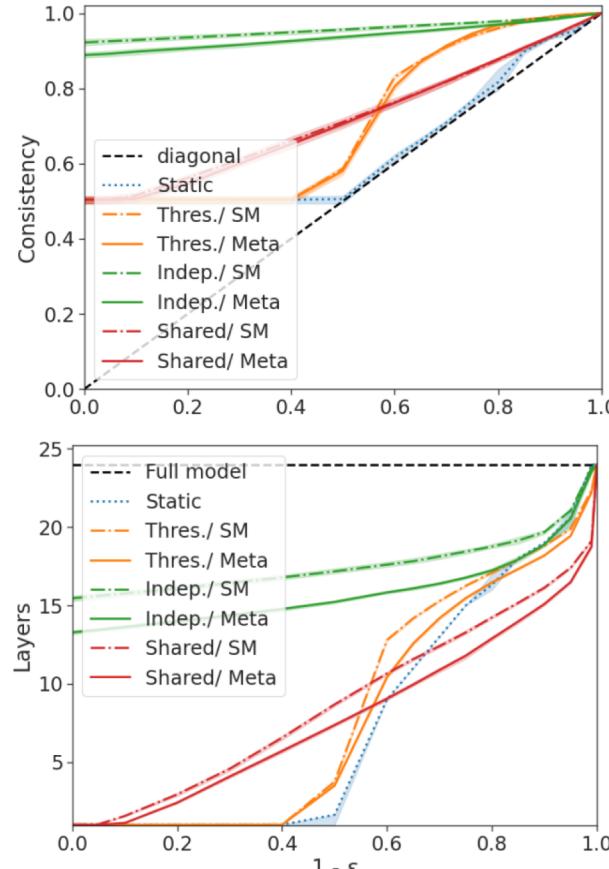
Metrics

- **Consistency:** Prediction is similar to F
- **Layers:** Number of Transformer layers used

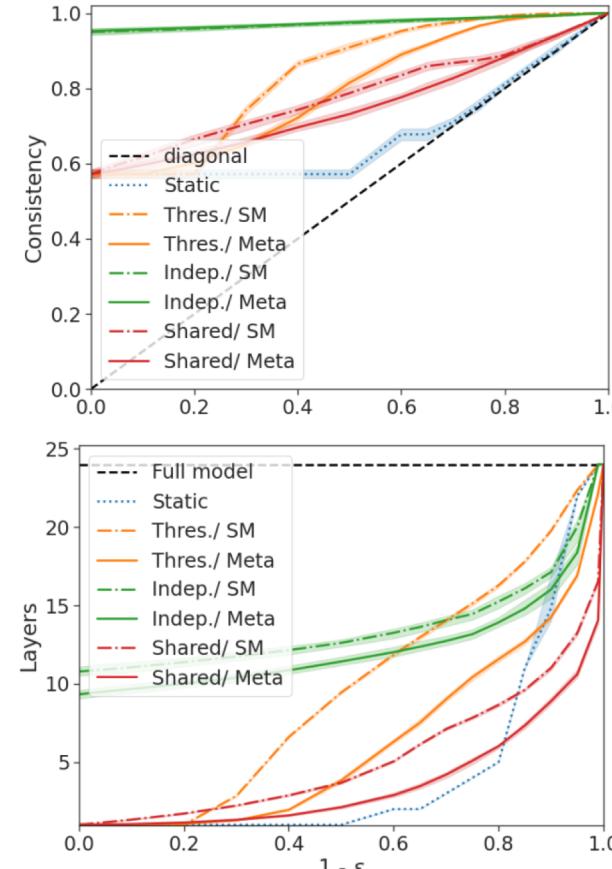
Results per ϵ (dev)



(a) IMDB



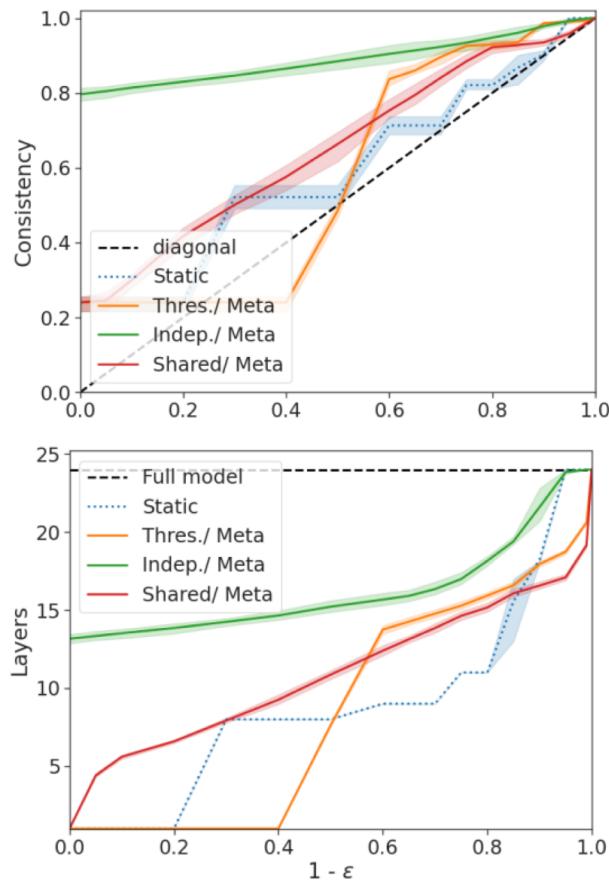
(b) VitaminC



(c) AG News

Results per ϵ (dev) – regression task

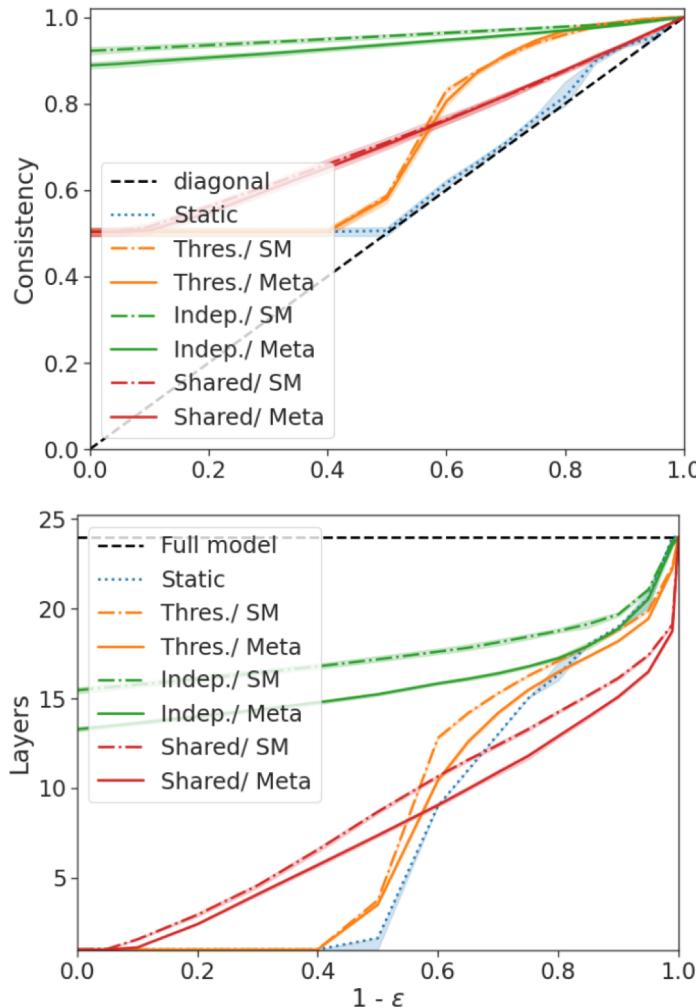
Softmax-based baselines are invalid



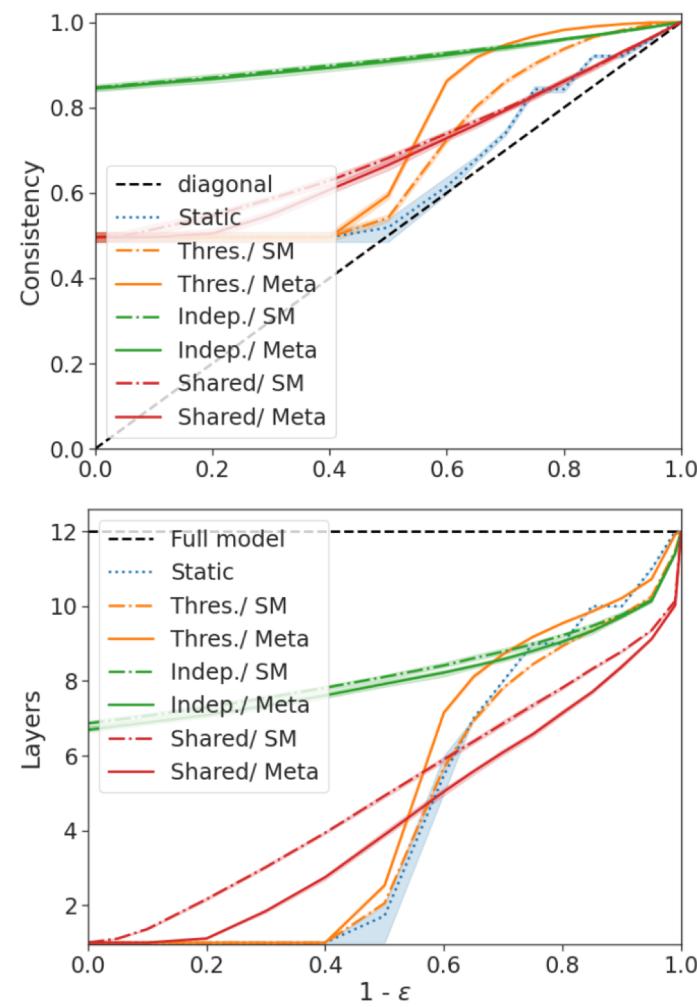
STS-B

Model agnostic performance

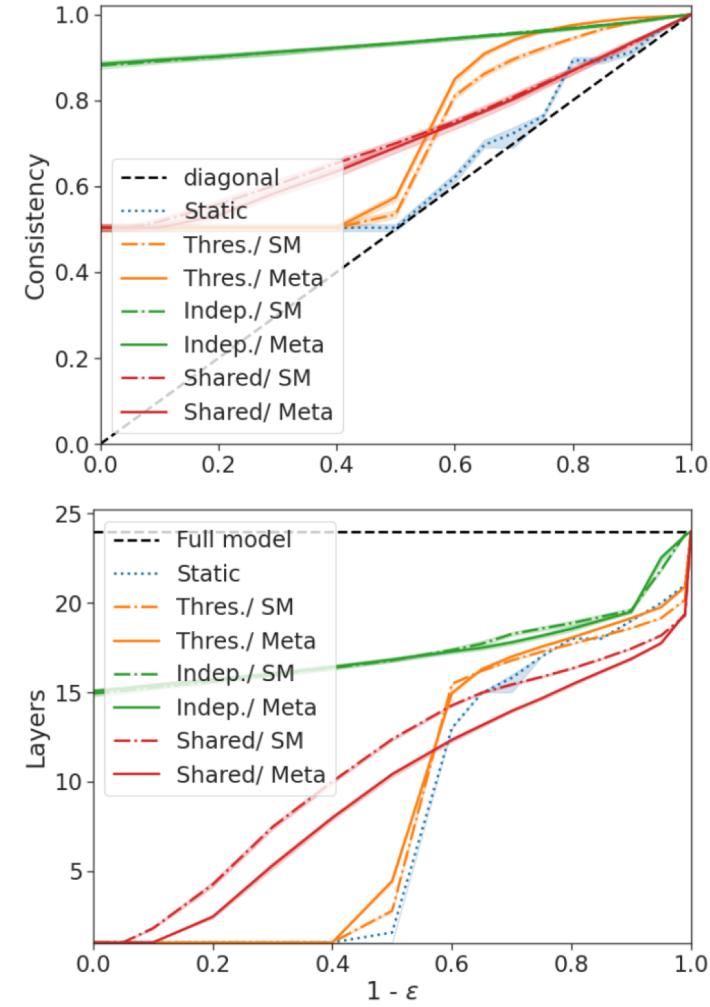
ALBERT-Xlarge



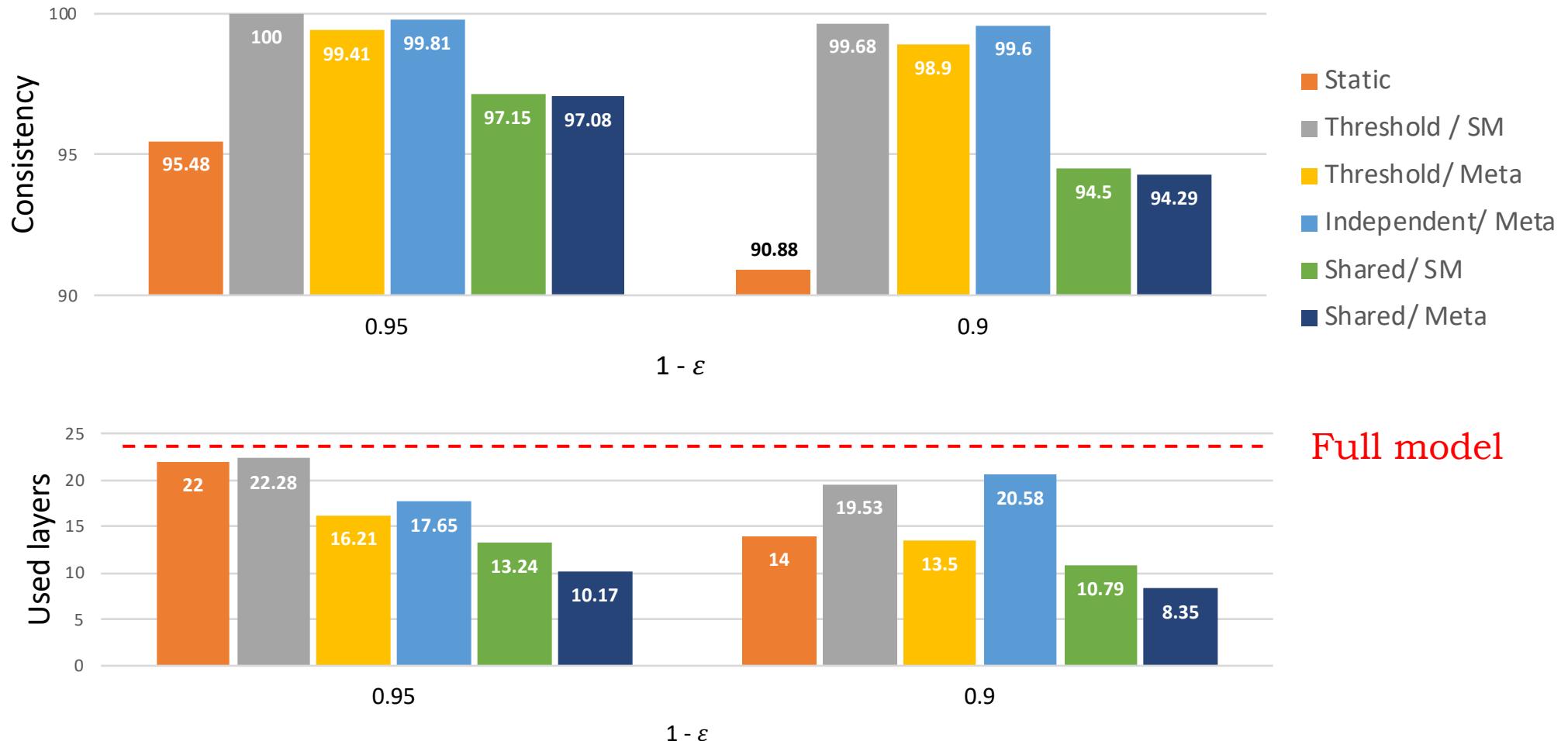
ALBERT-Base



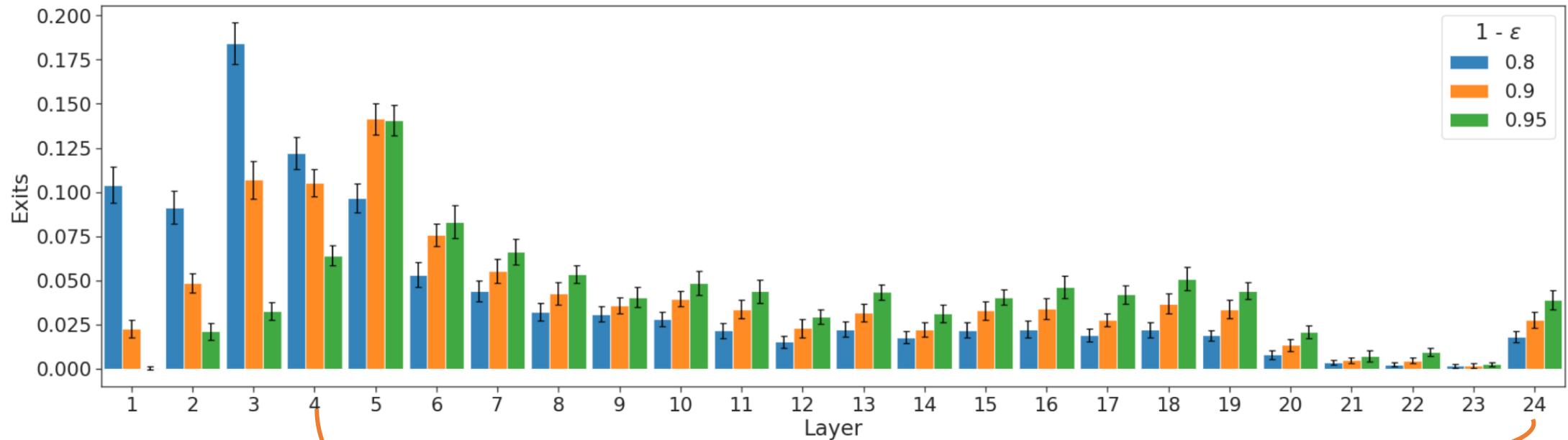
RoBERTa-Large



Example test results (AG news)



Exit layer distribution per ϵ (IMDB)

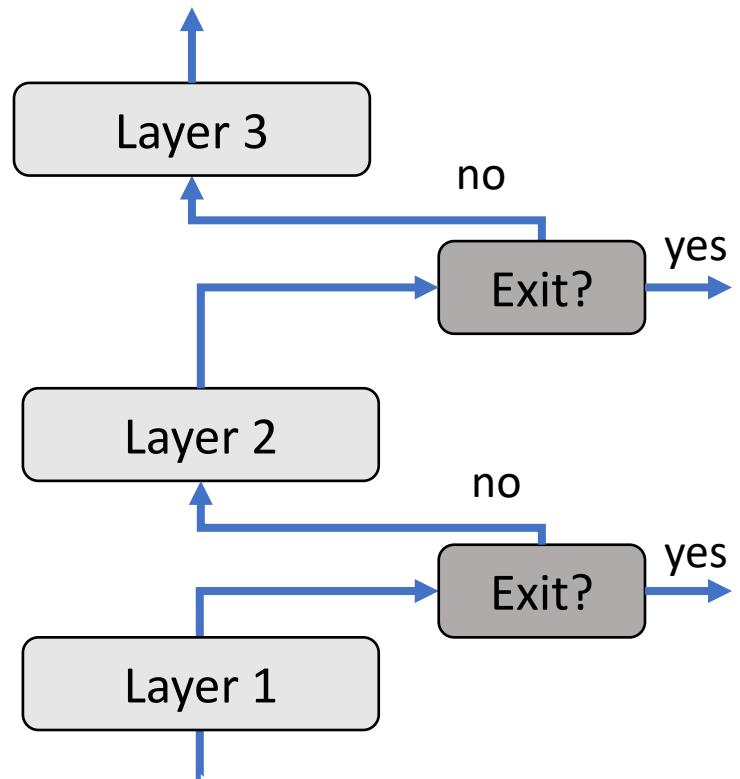


This movie was obscenely obvious and predictable. The scenes were **poorly** written and **acted even worse**.

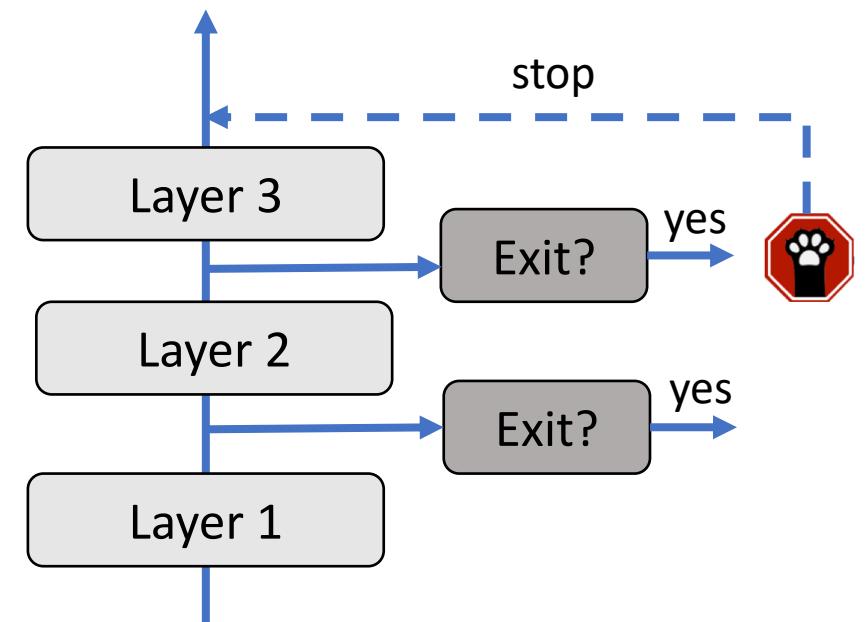
Hypothetical situations abound, one-time director Harry Ralston gives us the ultimate post-apocalyptic glimpse with the world dead...

Implementation options

Synchronous

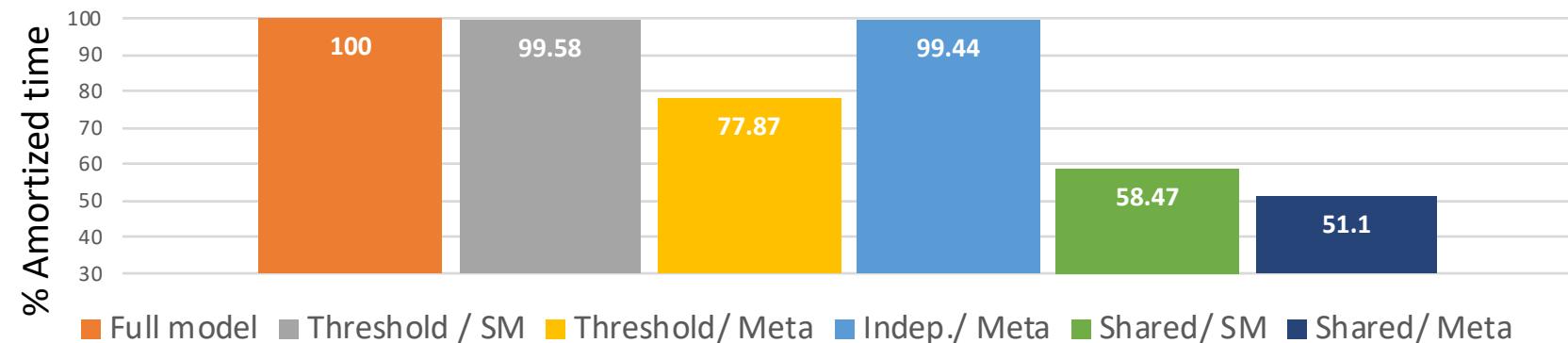


Concurrent

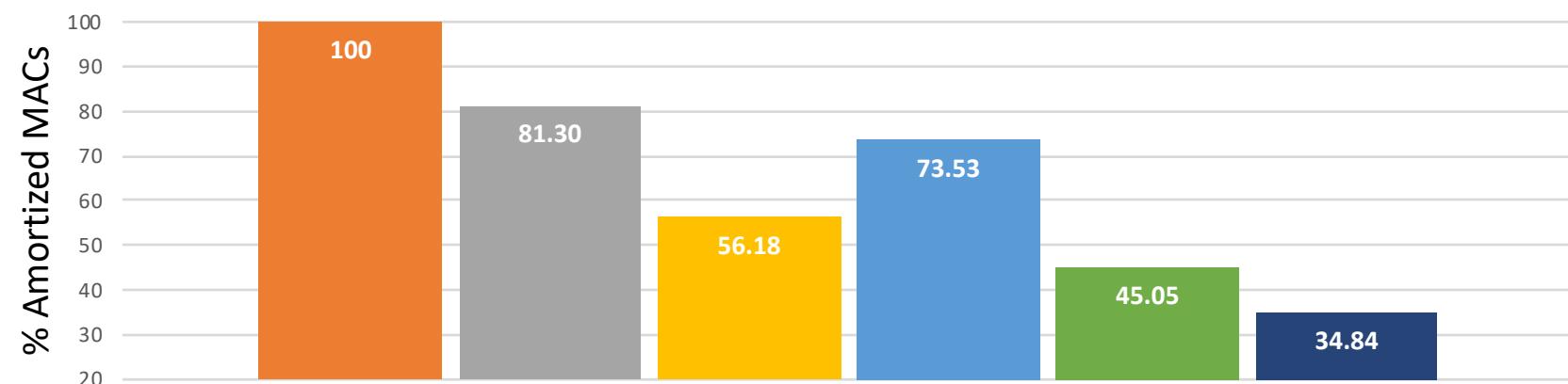


Speedup (AG news, $1 - \epsilon = 0.9$)

Amortized time (naïve synchronous implementation):



Amortized MACs:



Conclusion

- Dynamic computational effort per input “difficulty”
- Controllable consistency guarantees with the full model
- Meta early exit classifier
- Empirically demonstrated gains on four classification & regression tasks

Code: [Github.com/TalSchuster/CATs](https://github.com/TalSchuster/CATs)