# LogME: Practical Assessment of Pre-trained Models for Transfer Learning

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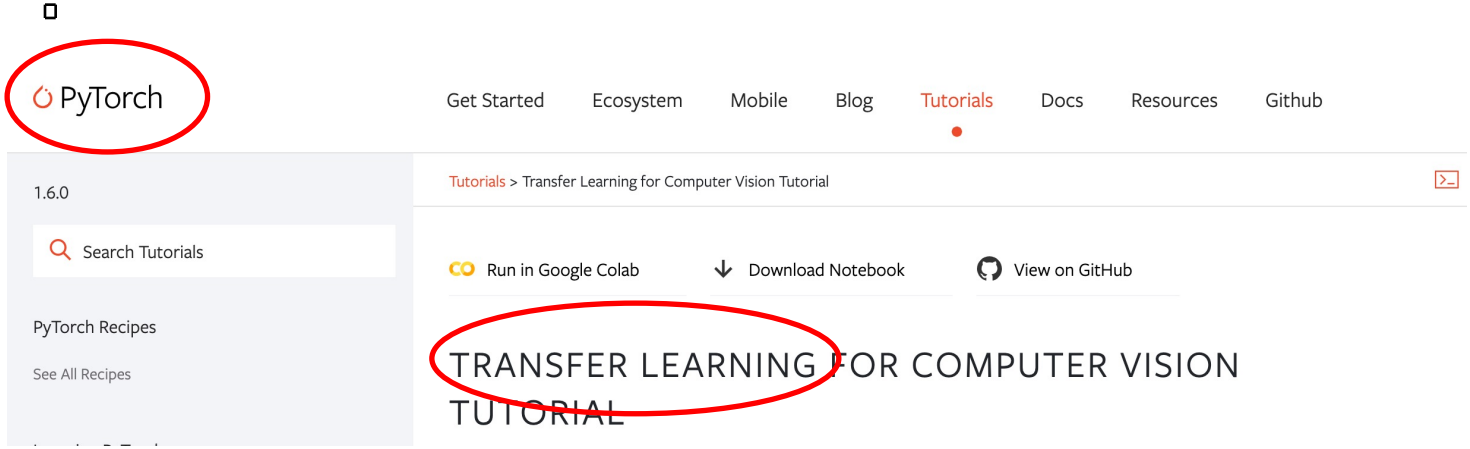
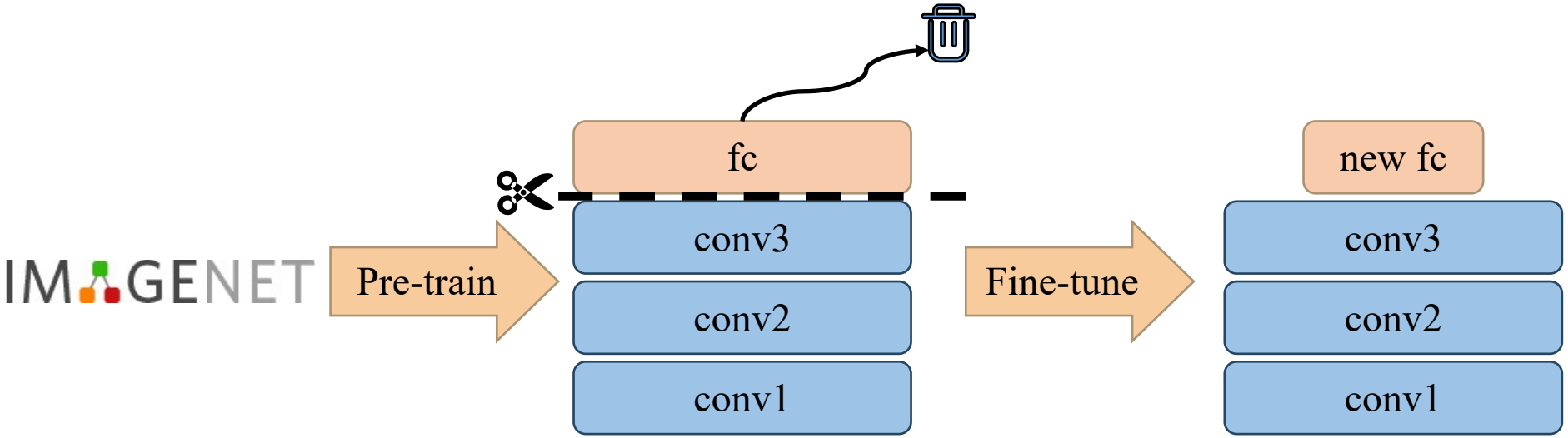
Wechat Blogpost (Chinese)

# Transfer Learning Paradigm

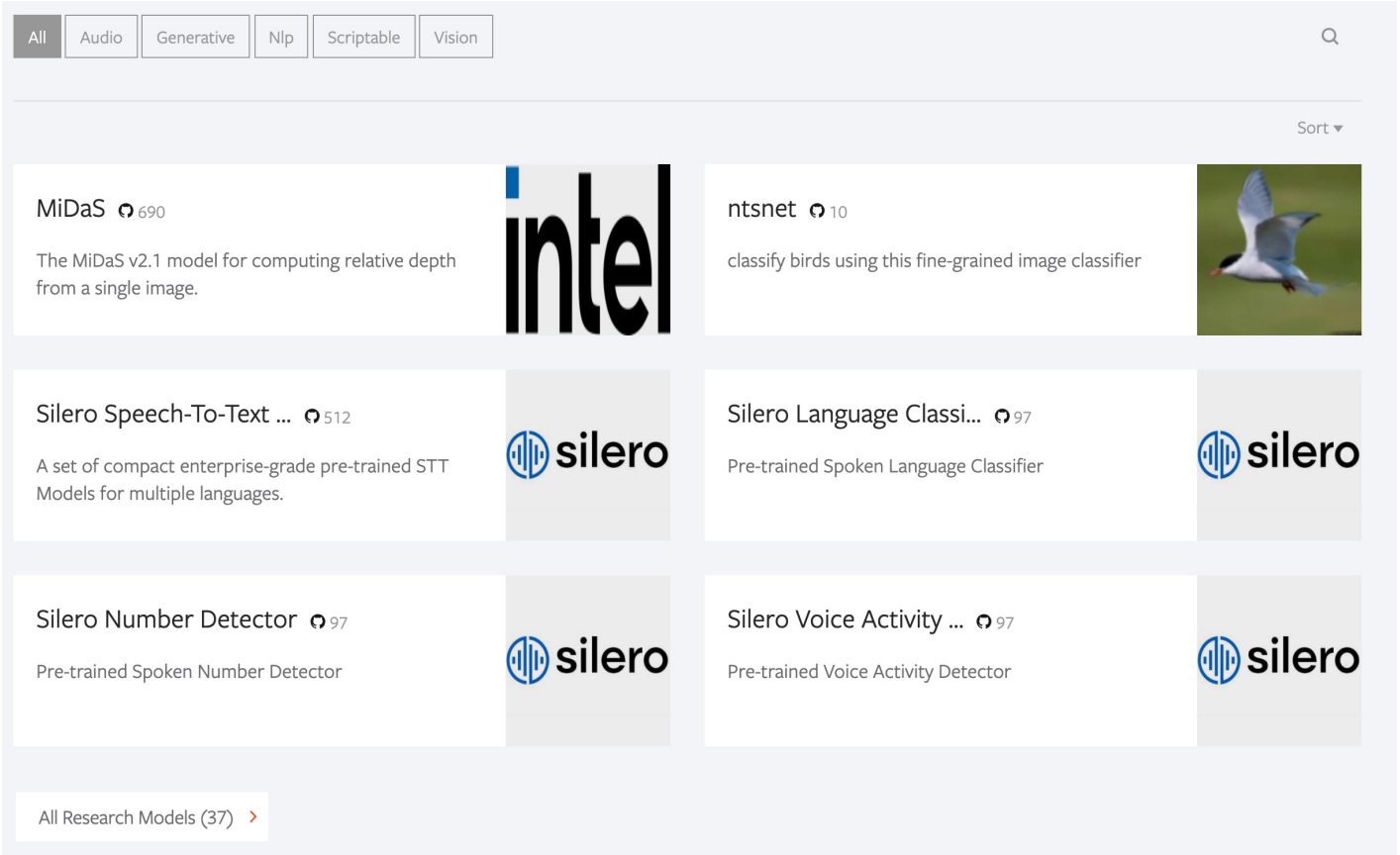



- Improve transfer learning with a given pre-trained model
  - Co-Tuning for Transfer Learning, NeurIPS 2020
  - Stochastic Normalization, NeurIPS 2020

# Pre-trained Model Selection

- Which pre-trained model to use?

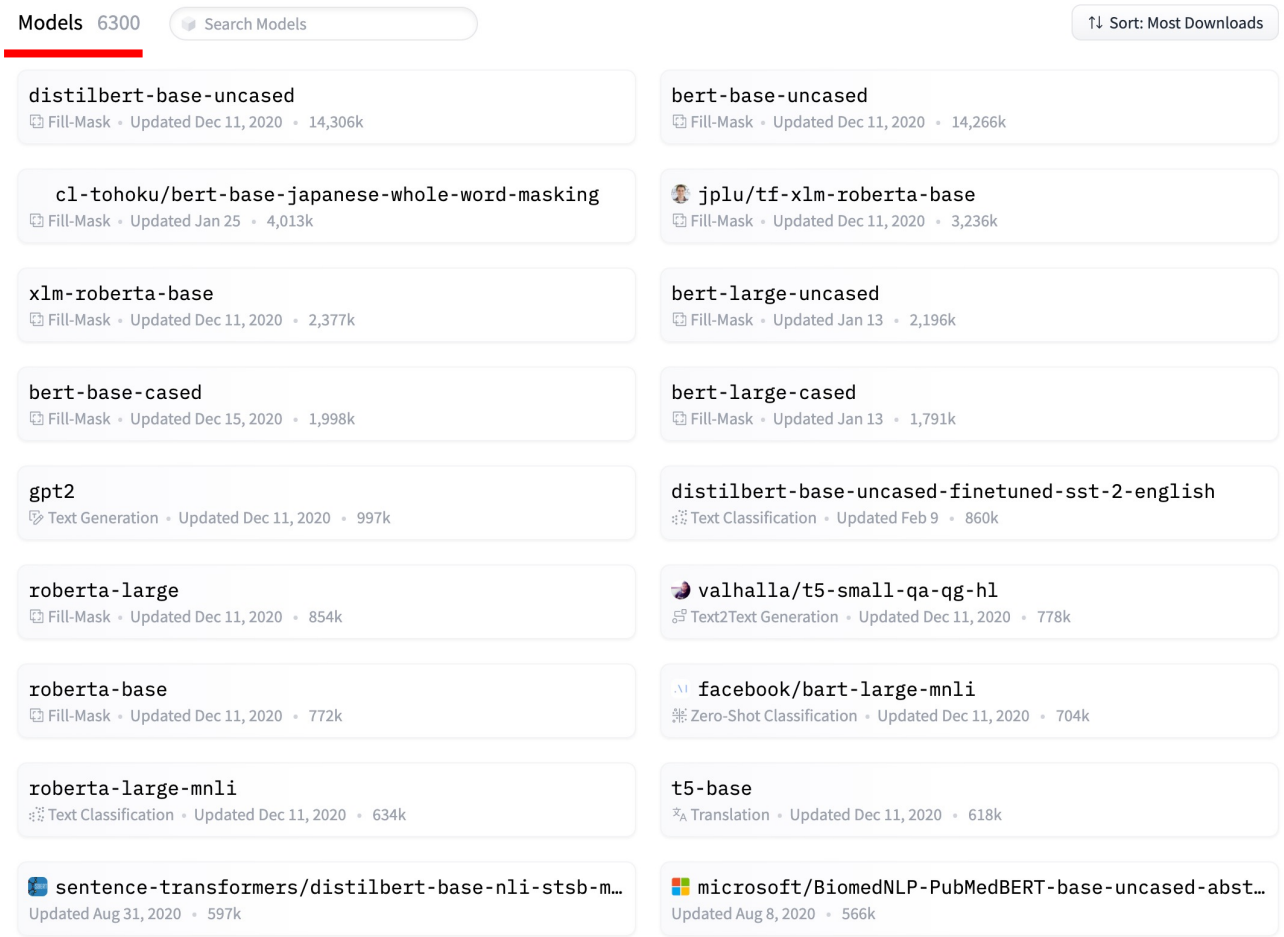



- AlexNet
- VGG
- ResNet
- SqueezeNet
- DenseNet
- Inception v3
- GoogLeNet
- ShuffleNet v2
- MobileNetV2
- MobileNetV3
- ResNeXt
- Wide ResNet
- MNASNet

- https://pytorch.org/hub/
- https://pytorch.org/vision/stable/models.html

# Pre-trained Model Selection

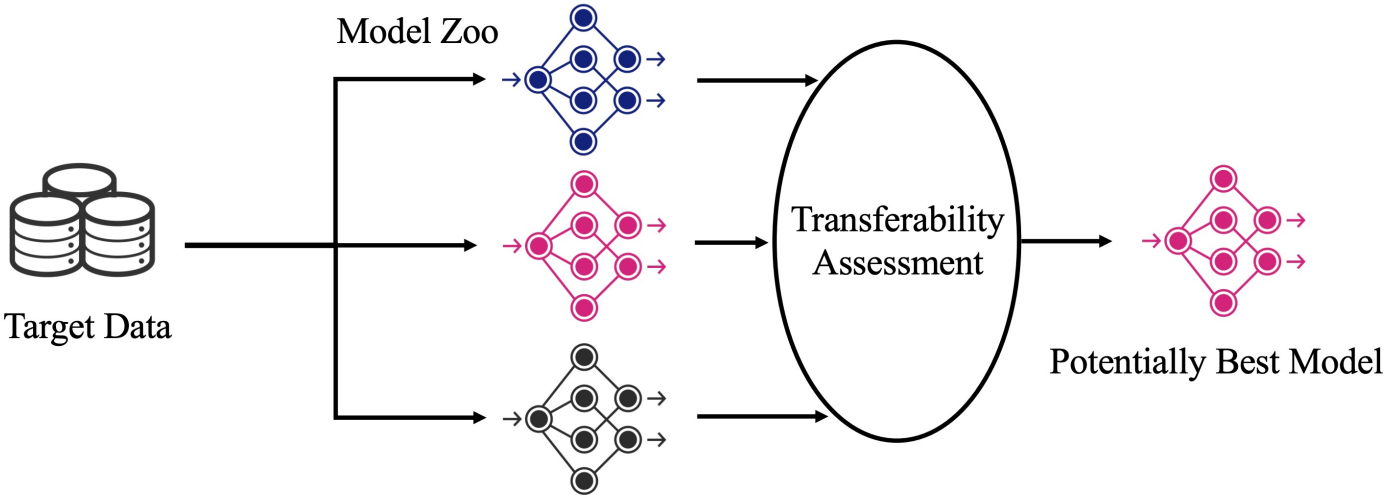
- Which pre-trained model to use? (6300 models)




- https://huggingface.co/models

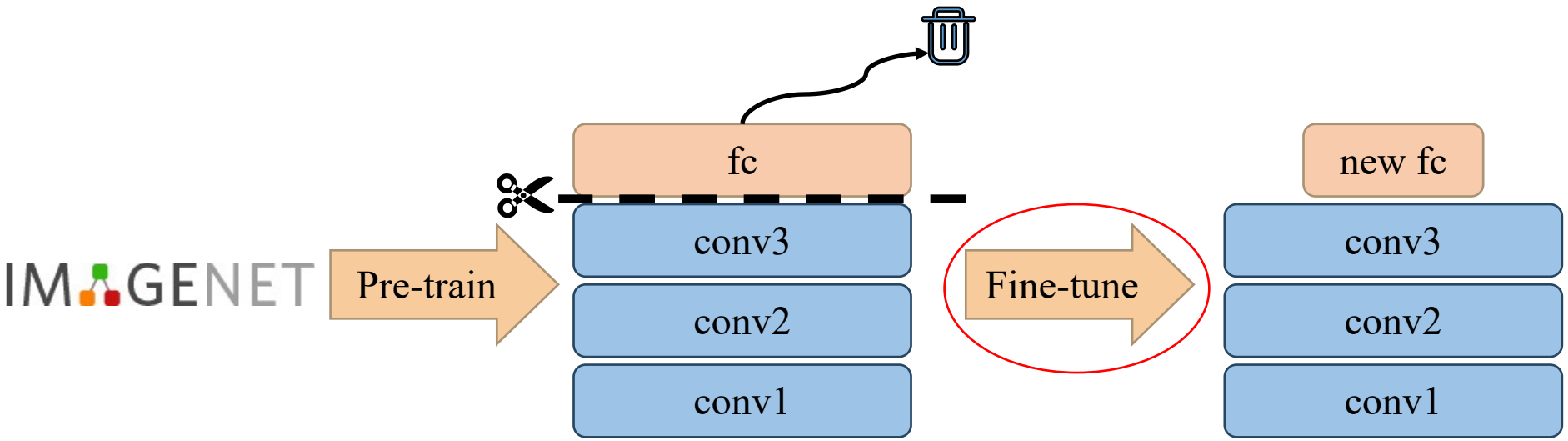
# Pre-trained Model Selection

- Porcedure of Pre-trained Model Selection



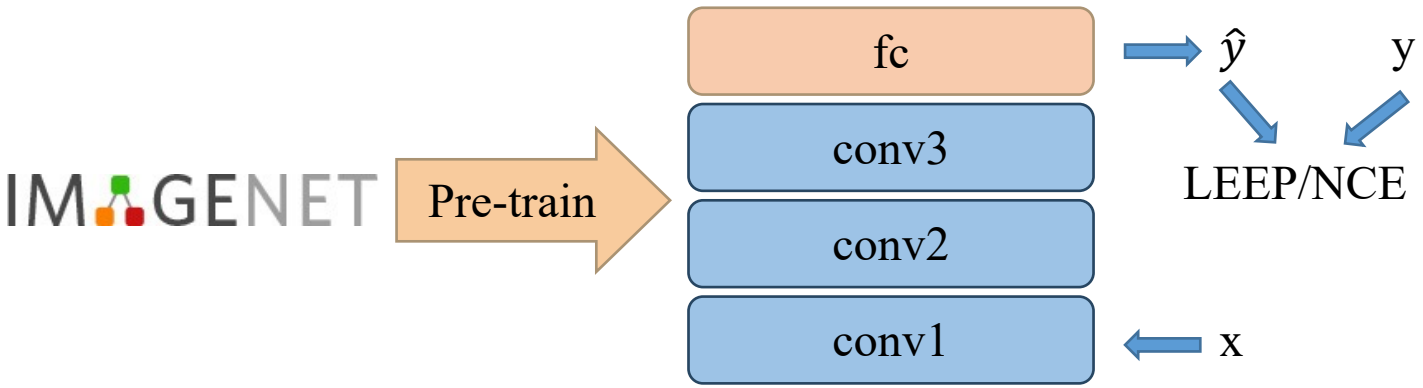

- How to measure correlation
  - M pre-trained models $\{\phi_m\}_{m=1}^{M}$ with a dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n}$
  - Ground truth transfer learning performance $\{T_m\}_{m=1}^{M}$
  - Assessment score $\{S_m\}_{m=1}^{M}$
  - weighted Kendall's Tau between $\{T_m\}_{m=1}^{M}$ and $\{S_m\}_{m=1}^{M}$

# Brute-force Fine-tuning



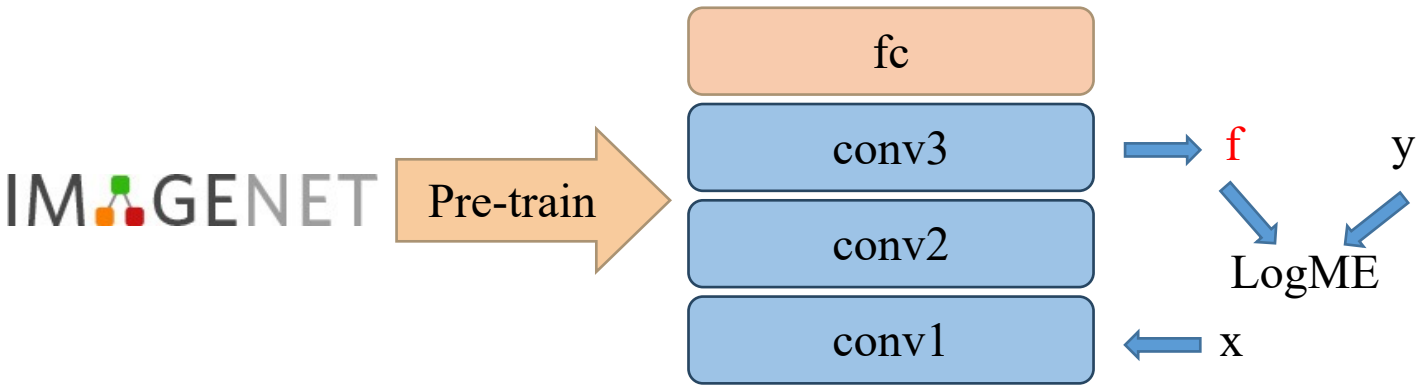

- complete fine-tuning of pre-trained models
  - hyper-parameter tuning, model training（☹ costly）
  - yield ground-truth measure（☺ $\tau_w = 1$）

# LEEP/NCE




- no training (☺ fast )
- build on category relationship
  - not accurate (☹ small $\tau_w$)
  - limited applicability ☹
  - can only transfer supervised pre-trained models to classification

# LogME (proposed)

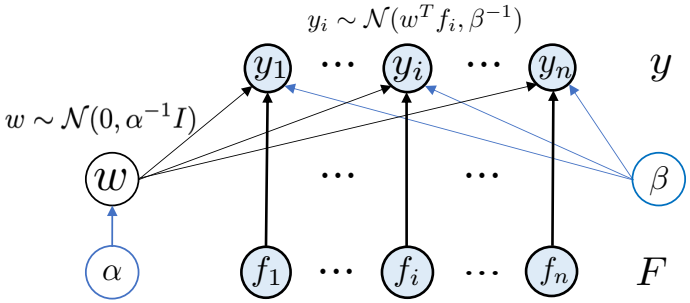



- fix pre-trained models ⇒ fast ☺
- treat pre-trained models as feature extractor
  - applicable to any pre-trained models ☺
- How to measure the compatibility between f and y?

# LogME – unary output

- measure by p(y|f) with linear model $y=w^T f$
- point estimation ☹
  - train optimal $w^*$， compute $p(y|f, w^*)$
  - prone to over-fitting
- distributional estimation (evidence) ☺
  - take expectation over all possible w with a causal graph

$$p(y|F) = \int p(w)p(y|F,w)\mathrm{d}w$$



# LogME – unary output

- Analytic form ( $A = \alpha I + \beta F^T F, m = \beta A^{-1} F^T y.$ )

$$\begin{aligned}\mathcal{L}(\alpha, \beta) &= \log p(y|F, \alpha, \beta) \\ &= \frac{n}{2}\log\beta + \frac{D}{2}\log\alpha - \frac{n}{2}\log 2\pi \\ &- \frac{\beta}{2}||Fm - y||_2^2 - \frac{\alpha}{2}m^T m - \frac{1}{2}\log|A|\end{aligned}$$

  - measures how likely labels are with respect to features.

- How to choose $\alpha, \beta$ ?
  - no grid search !
  - maximize $\mathcal{L}(\alpha, \beta)$ via alternative optimization

$$A = \alpha I + \beta F^T F, m = \beta A^{-1} F^T y, \gamma = \sum_{i=1}^{D} \frac{\beta\sigma_i}{\alpha + \beta\sigma_i}$$

$$\alpha \leftarrow \frac{\gamma}{m^T m}, \beta \leftarrow \frac{n - \gamma}{||Fm - y||_2^2}$$

  - name converged value LogME (log maximum evidence)

$$(\alpha^*, \beta^*) = \arg\max_{\alpha,\beta} \mathcal{L}(\alpha, \beta)$$

# LogME – complex cases

- Multivariate output
  - average LogME over each dimension
- classification with K classes
  - no analytic form with softmax output
  - regress one-hot labels instead

# Complexity Analysis

**Algorithm 1** LogME

1: **Input:** Pre-trained model $\phi$
Target dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^n$
2: **Output:** logarithm of maximum evidence (LogME)
3: Extract features using pre-trained model $\phi$:
$F \in \mathbb{R}^{n \times D}, f_i = \phi(x_i), Y \in \mathbb{R}^{n \times K}$
4: Compute SVD $F^T F = V \text{diag}\{\sigma\} V^T$
5: **for** $k = 1$ to $K$ **do**
6: Let $y = Y^{(k)} \in \mathbb{R}^n$, initialize $\alpha = 1, \beta = 1$
7: **while** $\alpha, \beta$ not converge **do**
8: Compute $\gamma = \sum_{i=1}^{D} \frac{\beta\sigma_i}{\alpha + \beta\sigma_i}, \Lambda = \text{diag}\{(\alpha + \beta\sigma)\}$
9: **Naïve**: $A = \alpha I + \beta F^T F, m = \beta A^{-1} F^T y$
10: **Optimized**: $m = \beta(V(\Lambda^{-1}(V^T(F^T y))))$
11: Update $\alpha \leftarrow \frac{\gamma}{m^T m}, \beta \leftarrow \frac{n - \gamma}{\|Fm - y\|_2^2}$
12: **end while**
13: Compute $\mathcal{L}_k = \frac{1}{n}\mathcal{L}(\alpha, \beta)$ using Eq. 2
14: **end for**
15: Return LogME $\frac{1}{K}\sum_{k=1}^{K} \mathcal{L}_k$

- complexity $\mathcal{O}(KD^3 + nKD^2)$
- for common cases

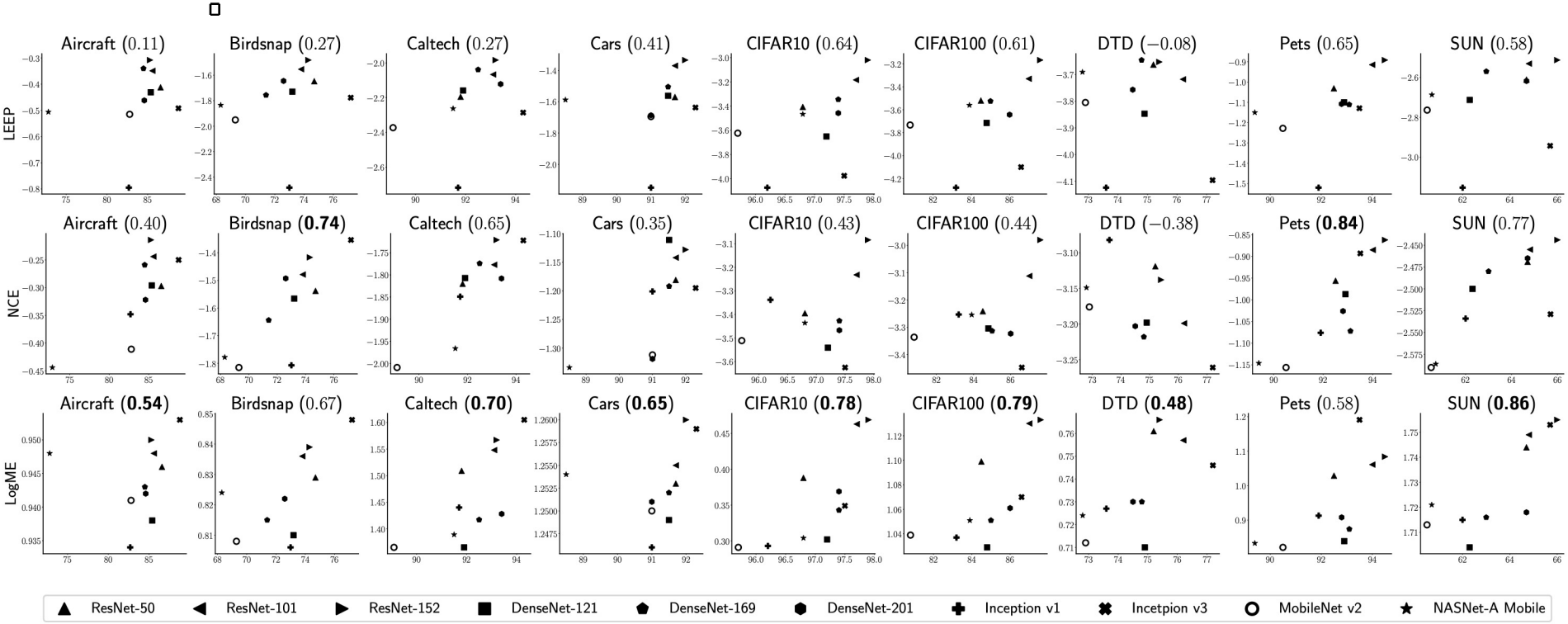
$$D \approx 10^3, n \approx 10^4, K \approx 10^3$$

$10^{13}$ operations needs $10^4$ seconds
not fast enough ☹

- bottleneck
  matrix inverse and MatMul (line 9)
- Optimization (line 10):
  - leverage results from line 4
  - avoid matrix inverse
  - MatMul → MatVecMul
  - reduce from $O(n^4)$ to $O(n^3)$

| | Complexity per for-loop | Overall complexity |
|---|---|---|
| naïve | $\mathcal{O}(D^3 + nD^2)$ | $\mathcal{O}(KD^3 + nKD^2)$ |
| optimized | $\mathcal{O}(D^2 + nD)$ | $\mathcal{O}(KD^2 + nKD + D^3 + nD^2)$ |

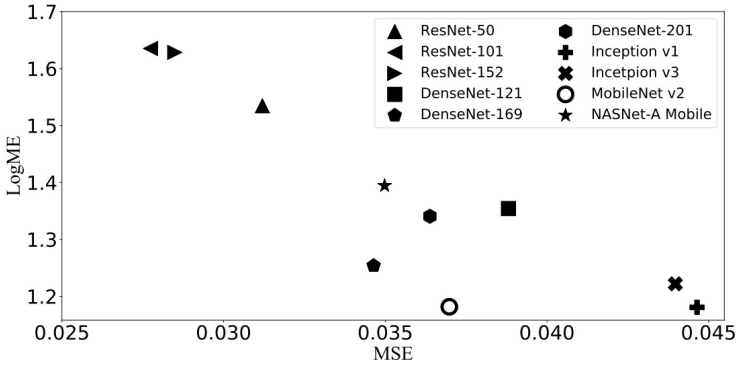
# Classification with Supervised Pre-trained Models




- 9 datasets, 10 pre-trained models
- x-axis (accuray) vs. y-axis (assessment score)
- LogME has largest $\tau_w$ in most tasks

# More experiments

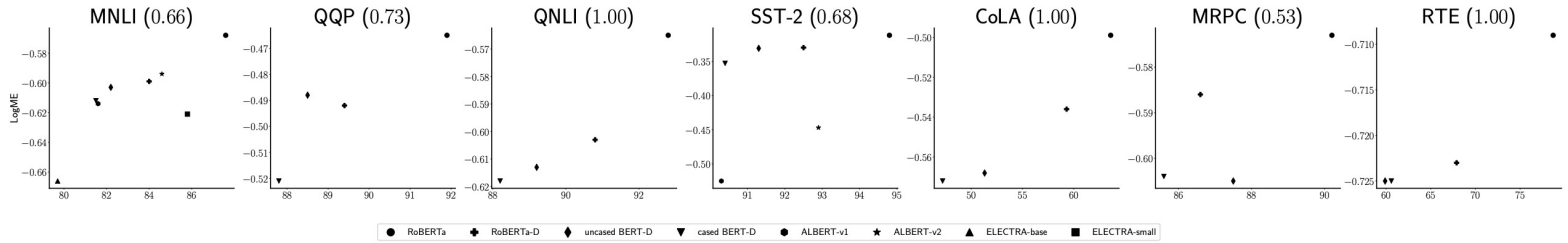
- Regression




- Contrastive pre-trained models

| Pre-trained Network | Aircraft | | dSprites | |
|---|---|---|---|---|
| | Accuracy (%) | LogME | MSE | LogME |
| MoCo V1 | 81.68 | 0.934 | 0.069 | 1.52 |
| MoCo V2 | 84.16 | 0.941 | 0.047 | 1.64 |
| MoCo 800 | 86.99 | 0.946 | 0.050 | 1.58 |
| SimCLR | 88.10 | 0.950 | - | - |
| | $\tau_w$: 1.0 | | $\tau_w$: 1.0 | |

- NLP models




- Only LogME works, LEEP / NCE are not applicable

# Efficiency of LogME

| | wall-clock time | | memory footprint | |
|---|---|---|---|---|
| Computer Vision | fine-tune (upper bound) | 161000s | fine-tune (upper bound) | 6.3 GB |
| | extract feature (lower bound) | 37s | extract feature (lower bound) | 43 MB |
| | LogME | 50s | LogME | 53 MB |
| | benefit | 3200 ↑ | benefit | 120 ↑ |
| Natural Language Processing | fine-tune (upper bound) | 100200s | fine-tune (upper bound) | 88 GB |
| | extract feature (lower bound) | 1130s | extract feature (lower bound) | 1.2 GB |
| | LogME | 1157s | LogME | 1.2 GB |
| | benefit | 86 ↑ | benefit | 73 ↑ |

- Much more efficient than brute-force fine-tuning
  - at most 3000x speedup with only 1% memory
  - almost lower bound

# Thanks for Listening!

Code Available: https://github.com/thuml/LogME