Multitask Learning, Overview of Some Other Topics, Conclusion and Take-aways

Piyush Rai

Introduction to Machine Learning (CS771A)

November 15, 2018

Announcement

- Final exam: Nov 29, 4pm-8pm (L18, L19, L20)

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- Project final report due on Nov 30

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- Multitask Learning
- Overview of some other topics
  - Learning Theory
  - Online Learning
  - Learning from time-series data
  - One-shot/few-shot learning
  - Zero-shot learning
  - Bias and Fairness
  - Interpretability of ML models
  - Model Compression

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- Basic clustering algorithms: K-means and extensions (e.g., soft K-means, kernel K-means)

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- Bias/Variance Trade-off, Some Practical Issues, Semi-supervised and Active Learning

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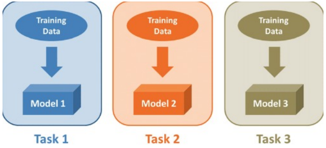
That's why the probabilistic viewpoint is important!

Multitask Learning

Multitask Learning

- In many learning problems, we wish to learn many models, each having its own data



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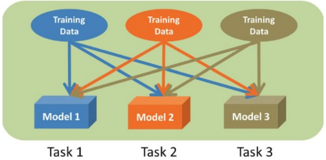

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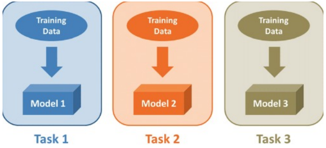

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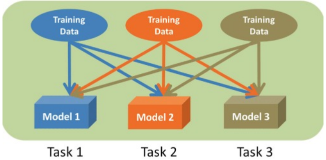

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- Example: We wish to learn spam classifiers for M users using each user's training data
- Multitask Learning is about designing ways to learn them jointly!

Multitask Learning: Formally

- Suppose we are given M datasets $(\mathbf{X}^{(1)}, \boldsymbol{y}^{(1)}), (\mathbf{X}^{(2)}, \boldsymbol{y}^{(2)}), \ldots, (\mathbf{X}^{(M)}, \boldsymbol{y}^{(M)})$

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- Usually okay to learn independently if we have plenty of training data for each learning task
- If training data per-task is very little and if tasks are related, it may not be the most ideal approach

Multitask Learning

- A better alternative will be to learn all the tasks jointly by minimizing the following loss function

$$\sum_{m=1}^{M} ||\boldsymbol{y}^{(m)} - \mathbf{X}^{(m)}\boldsymbol{w}_m||^2 + R(\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_M)$$

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- Example 2: Assume K groups with means $\boldsymbol{\mu}_1, \ldots, \boldsymbol{\mu}_K$ and each $\boldsymbol{w}_m$ to belong to one of the groups

$$R(\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_M) = \sum_{m=1}^{M} ||\boldsymbol{w}_m - \boldsymbol{\mu}_{z_m}||^2$$

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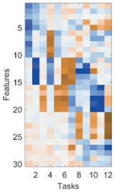
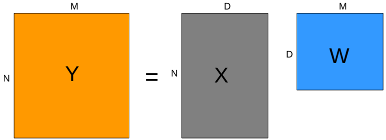
- Example 5: Assume all weight vectors to have same/similar sparsity pattern (relevant features)



Multitask Learning vs Multi-output/Multilabel Learning

- Multi-output and multi-label learning problems can also be thought of as multitask learning
- Same inputs and multiple outputs/labels to be predicted
- Here too, we need to learn a weight vector for each output/label
- The stadard approach is to simply model these as $\mathbf{Y} \approx \mathbf{XW}$ and solve for $\mathbf{W}$



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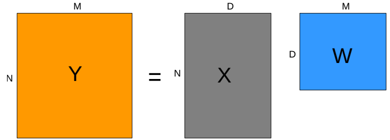

- We have seen that $\mathbf{W}$ has closed form solution if $\mathbf{Y}$ is real-valued

$$\mathbf{W} = (\mathbf{X}^\top \mathbf{X})^{-1}\mathbf{X}^\top \mathbf{Y} \qquad \text{(same as } \boldsymbol{w}_m = (\mathbf{X}^\top \mathbf{X})^{-1}\mathbf{X}^\top \boldsymbol{y}_m, \text{ for each m)}$$

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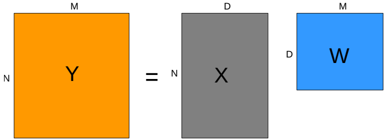

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Multitask Learning vs Multi-output/Multilabel Learning

- Multi-output and multi-label learning problems can also be thought of as multitask learning
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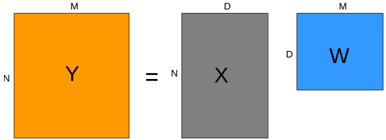

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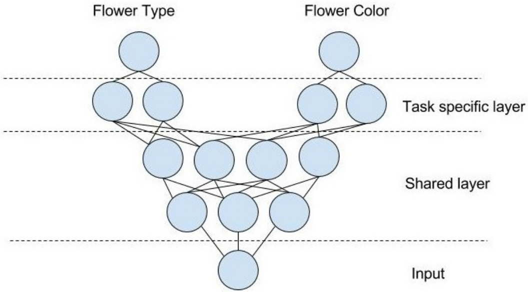
- However, the above apprpach is equivalent to treating each outputs/labels independently
- The ideas we saw today can be used to improve multi-output/multi-label learning

Multi-output/Multilabel Learning using Deep Neural Networks

- Deep neural networks are also popular these days for solving multi-output learning problems
- Basic idea: Have shared hidden layers to learn features that are good for predicting each output



- Such neural networks are called multitask neural networks

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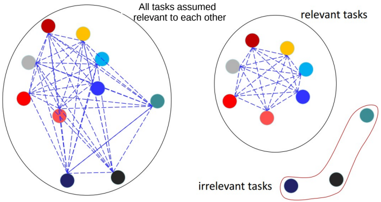

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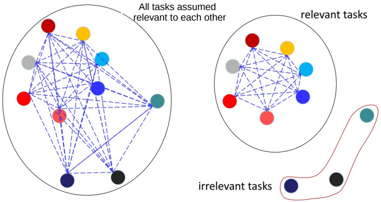

- Automatically learning how the tasks are related can help. There has been work on this too

Overview of Some Other Topics

Learning Theory

- Study of theoretical properties of learning models/algorithms, e.g.,
  - What is the generalization error (difference of test and training error) of some model?
  - What is the minimum number of training examples needed to get a certain accuracy?
  - What is learnable, what is not
- Some typical results from learning theory might look like this..

"size" or "complexity" of the class h belongs to

Test error of h   Training error of h

$$L_P(h) \leq L_{\mathcal{D}}(h) + \sqrt{\frac{\log |\mathcal{H}| + \log \frac{1}{\delta}}{2N}}$$

Number of training examples required to <= epsilon error

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- The field is too deep than what the above two equations convey :-)

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- Standard ML: Learn a model on some training data, apply it on a test data
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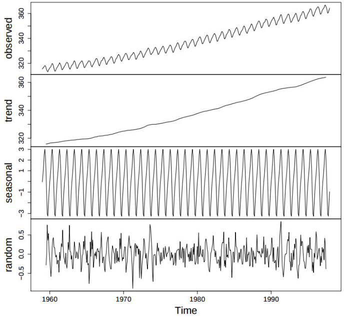
- This difference is known as "Regret" of the online learner

Modeling Time-Series Data

- The input is a sequence of (non-i.i.d.) examples $\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_T$
- The problem may be supervised or unsupervised, e.g.,
  - Forecasting: Predict $\boldsymbol{y}_{T+1}$, given $\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_T$
  - Cluster the examples or perform dimensionality reduction
- Evolution of time-series data can be attributed to several factors

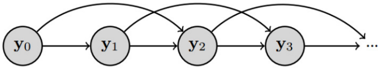


- Teasing apart these factors of variation is also an important problem

Modeling Time-Series Data (Contd)

- Auto-regressive (AR): Regress each example on p previous examples

$$\boldsymbol{y}_t = c + \sum_{i=1}^{p} w_i \boldsymbol{y}_{t-i} + \epsilon_t \qquad : \text{ An AR}(p) \text{ model}$$



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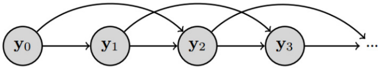

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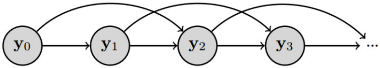

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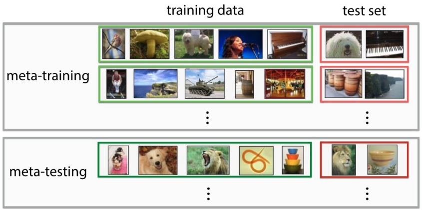

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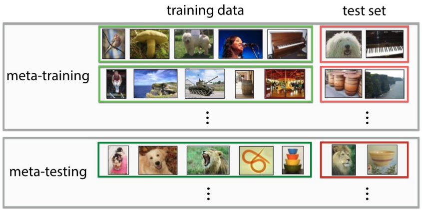

- The basic idea is to training in the same way we are expected to be tested (i.e., training using one example at a time, test, measure error, and repeat to improve)

Zero-Shot Learning

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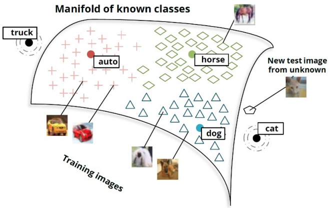

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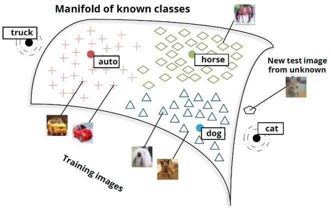

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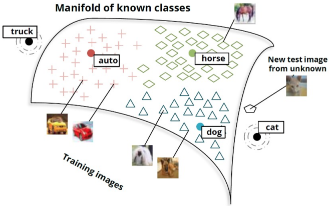

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  - Can learn a mapping from attribute vector to the parameters of the distribution of each class

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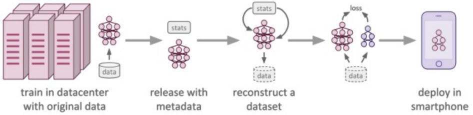

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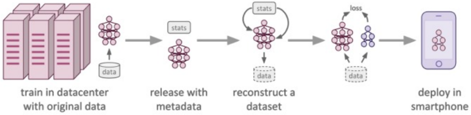

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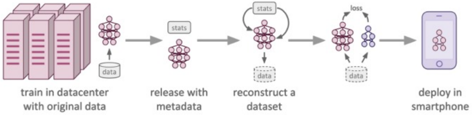

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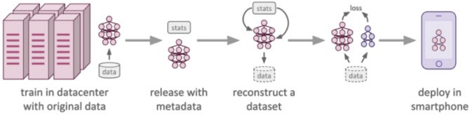

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- No free lunch. No learning algorithm is "universally" good.

Thank You! Have Fun Learning!