COST SENSITIVE CLASSIFICATION

**Batch policy optimization**

- **Target objective**: expected reward \( \max \sum x \cdot \pi(x) \)
- **Assume given complete data**
- **Target:**
  - \( \pi(x) \)
  - \( \pi(x) \)
- **Target vs surrogate optimization**
  - **Misclassification error on MNIST training data**

**Recall: supervised classification**

- **Target objective**: expected accuracy \( \max \sum x \cdot \log(\pi(x)) \)
- **Special case: engineered classification**
  - \( \pi(x) \)
  - \( \pi(x) \)
  - \( \pi(x) \)
- **What’s going on?**
  - \( \pi(x) \)
  - \( \pi(x) \)
  - \( \pi(x) \)
- **Useful properties of maximum likelihood**
  - \( \log(\pi(x)) \)
  - \( \log(\pi(x)) \)
  - \( \log(\pi(x)) \)

**Target vs surrogate optimization**

- **Misclassification error on MNIST training data**

**Comparing objectives**

**BATCH CONTEXTUAL BANDITS**

- **Coping with missing data**
  - **Optimization policy: \( \pi(x) \)**
  - **Missing data inference**
  - **Unified approach**

**BATCH CONTEXTUAL BANDITS**

- **Reward estimation**
  - For any \( x, c \), parameters \( \log(c) \cdot \hat{r} \)
  - \( \tilde{r}(x, c) = I_{(x)}(c) + 0c(x) \cdot \tilde{r}(x, c) \)

**Surrogate objectives**

- **Definition**: Optimal imputed local risk and suboptimality gap
  - \( \tilde{r}(x, c) = \min_{\hat{c}(x)} \tilde{r}(x, c) \)
  - \( \tilde{r}(x, c) \)

- **Proportion**: \( r \) \( \tilde{r}(x, c) \)
- **Theorem**: \( r \) \( \tilde{r}(x, c) \)
- **Optimization goal**: \( \tilde{r}(x, c) \)

**Unified approach**

- **Unified approach**:
  - \( \pi(x) \)
  - \( \pi(x) \)
  - \( \pi(x) \)

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1. Google Brain, 2. University of Alberta