Active Decision Boundary Annotation using Deep Generative Models

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Motivation: Annotation label scarcity

- Big-data age: Huge data sets readily available
- Machine learning requires annotated labels
- Labels often missing, or expensive to obtain
- Current research: Weak/semi/No-supervision
- Active learning: Ask for labels during training
Sampling instance labels in active learning

\[K\)-dimensional feature space embedding:
Sampling instance labels in active learning

$K$-dimensional feature space embedding:
Sampling instance labels in active learning

$K$-dimensional feature space embedding:
Active decision boundary annotation

In addition to labelling samples

We propose:

Also label the decision boundary
Active decision boundary annotation

*K*-dimensional feature space embedding:
Shoot a 1d line through feature space

$K$-dimensional feature space embedding:
Generate images along the 1d line

*K*-dimensional feature space embedding:

Generated row of images:
Where change: Near decision boundary
GAN: Generative Adversarial Networks

- Aim: learn to generate realistic data
- 2 networks: generator G; discriminator D

R: Real Data
G: Generator (Forger)
I: Input for Generator
D: Detective
GAN: Examples
Method

Unlabeled samples:
$G_z(x) = z$: encode images in latent space
Some labelled examples available

$G_z(x) = z$

Labeled samples:  □  ★  Unlabeled samples:  ●
Hypersphere $\Omega$ bounds samples

$G_z(x) = z$
Current estimate $\hat{\theta}$ of decision boundary

$G_z(x) = z$

$\Omega$

$\hat{\theta}$

Labeled samples: □ ★ Unlabeled samples: ●
Standard AL strategy: select sample $\mathbf{z}^*$

$$G_{\mathbf{z}}(\mathbf{x}) = \mathbf{z}$$

Labeled samples: ■ ★ Unlabeled samples: ●
$z^p$: Linearly project $z^*$ on $\hat{\theta}$

$G_z(x) = z$

$\Omega$

$\hat{\theta}$

$Labeled samples: \quad Unlabeled samples:
Query line $q$ through $z^*$ perpendicular to $\hat{\theta}$
Uniformly sample query line $q$ within $\Omega$
Generate image from \( z \) by \( G_{x}(z) = \hat{x} \)
Latent boundary annotation point: $z^p \cap \theta$
True decision boundary $\theta$

$G_z(x) = z$

$G_x(z) = \hat{x}$
Loss: add regression term

• We have annotated data samples $A$

• We also have boundary annotation points $B$

• Optimize Classification + Regression loss
Loss: add regression term

\( \mathcal{A} : \{(z^*, y)^N\} \): label pairs; \( \mathcal{B} : \{(z_q \cap \theta)^M\} \): annotations

Parametrize \( \hat{\theta} \) with a linear model, \( \hat{\mathbf{w}}^T \mathbf{z} + \hat{b} = 0 \)

Classification (hinge) loss on the labeled samples in \( \mathcal{A} \)

\[
\mathcal{L}_{\text{class}} = \frac{1}{|\mathcal{A}|} \sum_{(z,y) \in \mathcal{A}} \max \left( 0, 1 - y(\hat{\mathbf{w}}^T \mathbf{z} + \hat{b}) \right). \tag{1}
\]

Regression (square) loss to fit decision boundary through \( \mathcal{B} \)

\[
\mathcal{L}_{\text{regress}} = \frac{1}{|\mathcal{B}|} \sum_{\mathbf{z} \in \mathcal{B}} \left( \hat{\mathbf{w}}^T \mathbf{z} + \hat{b} \right)^2. \tag{2}
\]

Final (convex) loss \( \mathcal{L} = \frac{1}{2} \mathcal{L}_{\text{class}} + \frac{1}{2} \mathcal{L}_{\text{regress}} + \lambda \|\hat{\mathbf{w}}\|^2 \)
Exp 1: Evaluating generative model quality

- MNIST 0/8:
  - (a) Query lines with high human consistency.

- SVHN 0/8:
  - (b) Query lines with low human consistency.

- Shoe/Bag:
  - (a) Query lines with high human consistency.

(a) Query lines with high human consistency.

(b) Query lines with low human consistency.
Exp 1: Evaluating generative model quality

- For each set, ask 10 humans to annotate the same 10 lines.

Experiment 2: Evaluating inter-human annotations

<table>
<thead>
<tr>
<th></th>
<th>lines without change</th>
<th>samples deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>MNIST 0 vs. 8</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>SVHN 0 vs. 8</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Shoe-Bag</td>
<td>5</td>
<td>9</td>
</tr>
</tbody>
</table>

- Human consistency worse for the non-uniform Shoe-Bag set.
- Accurate (sigma < 4) for more uniform MNIST and SVHN sets.
Exp 2: Evaluating annotation noise

- Gaussian noise $\sigma \in \{1, \ldots, 5\}$ samples away from oracle.
- Repeated 15x; paired t-test for significance ($t < 0.05$)
- 150 (queries) is the max AULC Area Under Learning Curve

### Experiment 3: Evaluating annotation noise

<table>
<thead>
<tr>
<th>Noise (#im)</th>
<th>MNIST 0 vs. 8</th>
<th>SVHN 0 vs. 8</th>
<th>Shoe-Bag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sample</td>
<td>Boundary</td>
<td>Sample</td>
</tr>
<tr>
<td>$\sigma = 0$</td>
<td>144.2 ± 0.5</td>
<td>146.0 ± 0.3</td>
<td>119.1 ± 1.5</td>
</tr>
<tr>
<td>$\sigma = 1$</td>
<td>144.2 ± 0.5</td>
<td>145.9 ± 0.3</td>
<td>119.1 ± 1.5</td>
</tr>
<tr>
<td>$\sigma = 2$</td>
<td>144.2 ± 0.5</td>
<td>145.4 ± 0.5</td>
<td>119.1 ± 1.5</td>
</tr>
<tr>
<td>$\sigma = 3$</td>
<td>144.2 ± 0.5</td>
<td>145.0 ± 0.4</td>
<td>119.1 ± 1.5</td>
</tr>
<tr>
<td>$\sigma = 4$</td>
<td>144.2 ± 0.5</td>
<td>144.2 ± 0.4</td>
<td>119.1 ± 1.5</td>
</tr>
<tr>
<td>$\sigma = 5$</td>
<td><strong>144.2 ± 0.5</strong></td>
<td>143.6 ± 0.4</td>
<td>119.1 ± 1.5</td>
</tr>
</tbody>
</table>

- Results worsen with increasing noise
- Baseline becomes better around sigma = 4
- Matches human annotation accuracy
Exp 3: Does it generalize?

• Evaluate all classes in all datasets
• Repeated 5x; paired t-test for significance (t<0.05)
• 150 (queries) is the max AULC Area Under Learning Curve

<table>
<thead>
<tr>
<th>Experiment 5: Full dataset evaluation</th>
<th>Sample</th>
<th>Boundary (ours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MNIST</td>
<td>147.8 ± 0.06</td>
<td>148.3 ± 0.04</td>
</tr>
<tr>
<td>SVHN</td>
<td>127.8 ± 0.2</td>
<td>130.9 ± 1.9</td>
</tr>
<tr>
<td>Shoe-Bag</td>
<td>143.2 ± 0.6</td>
<td>145.4 ± 0.5</td>
</tr>
</tbody>
</table>

• For all datasets our method significantly improves over sample-based active learning.
Summary & Conclusion

1. Extend active learning with decision boundary annotation.
2. Synthesize new images along a 1-dimensional query line.
3. Ask oracle to annotate point where the images change class.

- **Disadvantage:** Visual domain only
- **Disadvantage:** Critically depend on generator
- **Challenge:** Large margins; possibly annotate margin?
- **Challenge:** Non-linearity in query-line and decision-boundary

**Conclusion:** Boundary annotations improve over sample annotations only. Future work needed to address challenges and limitations.