Annotation-Informed Modeling I

Training Models on Annotated Data

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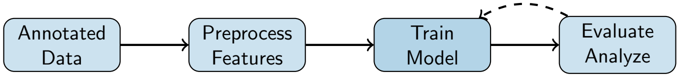
Today's Agenda

1. Welcome back from Passover break
2. Training models on annotated data
3. Handling annotation uncertainty
4. Multi-annotator learning
5. Soft labels vs. hard labels
6. Comparing human vs. LLM annotations

Project: Gold standard dataset due
Assignment: HW 4 assigned

The Modeling Pipeline



Today's focus: How annotation quality affects each stage

Standard Training Approach

Using adjudicated gold standard:

1. Take gold label for each instance
2. Split into train/dev/test
3. Train model to predict labels
4. Evaluate on test set

Assumes:

- Single correct label exists
- Gold standard is reliable
- All instances equally informative

But: What about annotation uncertainty?

Handling Annotation Uncertainty

Disagreement carries information

Options:

1. **Ignore uncertainty:** Use gold labels only
2. **Filter uncertain:** Remove low-agreement items
3. **Weight by agreement:** Confident examples matter more
4. **Soft labels:** Train on label distributions
5. **Multi-task:** Model uncertainty explicitly

Key insight: Uncertain examples may be legitimately ambiguous

Soft Labels

Instead of single label, use distribution

Hard label:

- "This is POSITIVE" (one-hot: [1, 0, 0])

Soft label:

- "60% POSITIVE, 30% NEUTRAL, 10% NEGATIVE"
- Label distribution: [0.6, 0.3, 0.1]

From annotator votes:

- 3 annotators: 2 say Positive, 1 says Neutral
- Soft label: [0.67, 0.33, 0]

Training with Soft Labels

Standard cross-entropy loss:

$$L = -\sum_c y_c \log(p_c)$$

Where y is one-hot (hard label)

With soft labels:

$$L = -\sum_c \hat{y}_c \log(p_c)$$

Where $\hat{y}$ is the label distribution

Effect:

- Model learns nuance in uncertain cases
- Less confident predictions for ambiguous items
- Can improve generalization

Multi-Annotator Learning

Don't aggregate – model all annotators

Approaches:

1. **Data augmentation:** Treat each annotation as separate training example
2. **Multi-task learning:** Predict each annotator's label
3. **Annotator modeling:** Learn annotator-specific biases
4. **Ensemble:** Train separate models, combine predictions

Benefits:

- Captures systematic disagreement
- Models perspective diversity
- Better for subjective tasks

Data Augmentation Approach

Simple multi-annotator learning:

Original:

- Text: “Not bad at all”
- Annotations: [Pos, Pos, Neu]

Augmented training data:

- (“Not bad at all”, Positive)
- (“Not bad at all”, Positive)
- (“Not bad at all”, Neutral)

Effect: Model sees all perspectives during training

Human vs. LLM Annotations

Comparing annotation sources

Experiment design:

1. Annotate same data with humans AND LLM
2. Train separate models on each
3. Evaluate both on human-annotated test set
4. Compare performance

Key finding (various studies):

- LLM-trained models often comparable for simple tasks
- Human annotations better for subjective/complex tasks
- Combined often best

When LLM Annotations Work

For model training:

Good scenarios:

- Large training set needed
- Task is objective with clear criteria
- Domain is well-represented in LLM training
- Small quality drop is acceptable

Poor scenarios:

- High-stakes application
- Subjective judgment required
- Novel domain
- Training benchmark models

Practical Considerations

Model selection:

- Start simple (Logistic Regression, SVM)
- Establish baseline before complex models
- Consider data size (transformers need more)

Hyperparameter tuning:

- Use dev set, not test set
- Report best dev configuration
- Don't overfit to dev set

Reproducibility:

- Set random seeds
- Document all preprocessing
- Release code and data

Baseline Models

Always establish baselines:

Simple baselines:

- Most frequent class (majority baseline)
- Random prediction
- Simple rules

Standard ML baselines:

- Bag of Words + Logistic Regression
- TF-IDF + SVM
- FastText

Then consider:

- BERT/RoBERTa fine-tuning
- Domain-specific models

Semester Project: Modeling

For your project:

1. Train at least one model on your gold standard
2. Report baseline performance
3. Analyze errors
4. Connect to annotation quality

Questions to address:

- Does model performance match IAA?
- Which categories are harder?
- What errors does the model make?
- How would you improve annotation?

Next Class: Modeling and Evaluation II

Lecture 22 (Apr 15): Annotation-Informed Modeling II

Topics:

- Evaluation metrics for annotated tasks
- Precision, Recall, F1 for various task types
- Error analysis using annotations
- LLM-as-judge evaluation
- Building evaluation benchmarks

Key Takeaways

1. **Standard training** uses gold labels, ignoring uncertainty
2. **Soft labels** capture annotation distributions
3. **Multi-annotator learning** models all perspectives
4. **LLM annotations** can work for training simple task models
5. **Always establish baselines** before complex models
6. **Model performance** is bounded by annotation quality

Questions?

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Office Hours: Wednesdays 1-3pm, Volen 109

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