Annotation Tools Advanced

Feature Engineering

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Today's Agenda

1. Argilla for RLHF data collection
2. Custom annotation interfaces
3. From annotations to features
4. Feature engineering for NLP
5. Representation learning
6. Handling rare classes

Project: Draft 2 guidelines due
Assignment: HW 2 due

Argilla: For RLHF and Feedback

Designed specifically for LLM workflows

Key features:

- Native preference annotation support
- Hugging Face ecosystem integration
- Built-in weak supervision
- Collaborative feedback collection
- Active learning capabilities

Best for:

- RLHF preference data
- LLM evaluation and red-teaming
- Human-AI collaborative annotation
- Feedback collection at scale

Argilla vs. Label Studio

Feature	Label Studio	Argilla
General annotation	✓	✓
Multi-modal	✓✓	✓
Preference annotation	Limited	✓✓
RLHF workflows	Limited	✓✓
Hugging Face integration	✓	✓✓
Active learning	✓	✓
Self-hosted	✓	✓

Choose based on your task:

- General NLP annotation → Label Studio
- RLHF/preference data → Argilla
- Multi-modal → Label Studio

Custom Annotation Interfaces

When built-in tools aren't enough:

Options:

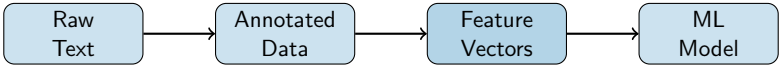
1. **Extend existing tools:** Custom Label Studio templates
2. **Streamlit/Gradio:** Quick web interfaces
3. **Custom web app:** Full control, more effort
4. **Jupyter notebooks:** Interactive annotation

When to build custom:

- Unique annotation type
- Complex workflows
- Integration with specific systems
- Special visualization needs

From Annotations to Features

ML models need features, not raw annotations



Feature engineering: Converting text + annotations to numbers

Basic Text Features

Bag of Words (BoW):

- Each word is a feature
- Count or binary occurrence
- Simple but effective baseline

Example:
"I love this movie" $\rightarrow$ [I:1, love:1, this:1, movie:1]

TF-IDF:

- Weight by term frequency $\times$ inverse document frequency
- Down-weights common words
- Up-weights distinctive words

Feature Matrix

Representing features as a matrix:

	charming	delightfully	hollow	picture	uplifting	...
"A pleasant..."	0	0	0	1	1	...
"A charming..."	1	1	0	0	0	...
"A hollow..."	0	0	1	0	0	...

Sparse representation: Most entries are 0

In Python: Use `scipy.sparse` or `DictVectorizer`

Additional Features

Beyond bag of words:

- **N-grams:** Word pairs/triples ("not good" vs. "good")
- **Character n-grams:** Subword patterns
- **Length features:** Word count, sentence count
- **Lexical features:** Punctuation, capitalization
- **Metadata:** Time, author, source

Feature binning:

- Convert continuous to categorical
- Example: length $\rightarrow$ short/medium/long
- Reduces dimensionality

Scikit-Learn DictVectorizer

Convert feature dictionaries to matrices:

```
from sklearn.feature_extraction import DictVectorizer
```

Input:

- List of dictionaries
- Each dict: {feature: value}

Output:

- Sparse matrix
- Each row = one instance
- Each column = one feature

Handles: Both numeric and categorical features

Feature Weights in Classification

Models learn weights for features:

Feature	Positive weight	Negative weight
“charming”	3.0	0.5
“delightful”	2.0	0.2
“hollow”	-0.4	2.4
“terrible”	-1.5	3.5

Prediction: Weighted sum of feature values

Learning algorithms: Naive Bayes, Logistic Regression, SVM
These are covered in COSI 114b and 134

Handling Rare Classes

Problem: Some labels have few examples

Options:

1. **Merge classes:** Combine rare labels into "Other"
2. **Remove:** Drop if not essential to task
3. **Oversample:** Duplicate rare examples
4. **Undersample:** Reduce frequent examples
5. **Weighted loss:** Penalize errors on rare classes more
6. **Better models:** SVM, SetFit handle imbalance better

Key question: Is the rare class important for your task?

Filtering Vocabulary

Zipf's Law: Most words are rare

Problem:

- Most frequent words may be uninformative ("the", "a")
- Least frequent words have too few examples to learn from
- Full vocabulary = slow model training

Solutions:

- Remove stopwords
- Set minimum document frequency (ignore very rare)
- Set maximum document frequency (ignore very common)
- Limit total vocabulary size

Modern Representations

Beyond bag of words:

Word embeddings:

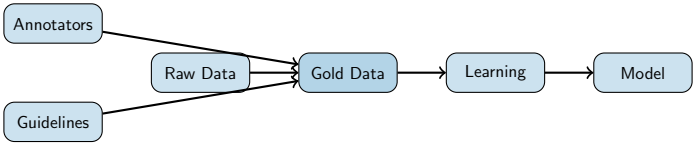
- Word2Vec, GloVe
- Dense vectors (300 dimensions)
- Capture semantic similarity

Contextual embeddings:

- BERT, RoBERTa, GPT
- Different representation per context
- State-of-the-art performance

For this course: Focus on annotations, use pre-built models

Blueprint: Annotation to Model



Key insight: Annotation quality affects model quality
"Garbage in, garbage out"

Next Class: Human-AI Collaboration

Lecture 17 (Mar 18): Human-AI Collaborative Annotation

Topics:

- Human-in-the-loop paradigm
- LLM pre-annotation + human correction
- Active learning with LLMs
- Efficiency gains from hybrid approaches
- When to trust LLM annotations

Project: Continue annotation work

Key Takeaways

1. **Argilla** is designed for RLHF and preference data
2. **Feature engineering** converts text to numbers for ML
3. **Bag of words** is simple but effective baseline
4. **Rare classes** need special handling
5. **Vocabulary filtering** improves efficiency
6. **Modern embeddings** (BERT) often outperform BoW

Questions?

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