Preference Data & RLHF Annotation

Aligning Language Models with Human Values

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Today's Agenda

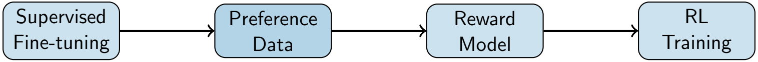
1. Introduction to RLHF
2. The preference annotation task
3. Reward modeling data collection
4. Constitutional AI
5. Direct Preference Optimization (DPO)
6. Practical considerations

Assignment: HW 4 due this week

What is RLHF?

Reinforcement Learning from Human Feedback

Goal: Align LLM behavior with human preferences



Key insight: Preferences are easier to annotate than demonstrations

Why Preferences?

Comparing is easier than generating

Demonstration annotation:

- “Write the ideal response to this prompt”
- Requires expertise to write good responses
- Time-consuming
- Single point of reference

Preference annotation:

- “Which response is better?”
- Easier cognitive task
- Faster annotation
- Captures relative quality

Preference Annotation Task

Given: A prompt and two (or more) responses
Task: Indicate which response is better

Example

Prompt: "Explain photosynthesis simply."
Response A: "Plants convert sunlight into food..." (accurate, clear)
Response B: "It's a complex biochemical process involving..." (accurate, verbose)

Annotation: A $>$ B (A is preferred)

Preference Data Formats

Common formats:

1. **Binary comparison:**
   - A wins, B wins, or tie
   - Simple, clear
2. **Rating scale:**
   - Rate each response 1-5
   - More information but harder to calibrate
3. **Ranking:**
   - Order multiple responses
   - Rich signal, more complex annotation
4. **Best-of-N:**
   - Select best from N options
   - Efficient for data collection

What Makes a Response "Better"?

Common evaluation criteria (InstructGPT):

1. **Helpful:** Provides useful information
2. **Harmless:** Avoids dangerous or unethical content
3. **Honest:** Accurate and doesn't hallucinate

Additional criteria:

- Follows instructions
- Appropriate length
- Clear and well-organized
- Appropriate tone

Challenge: Criteria can conflict (helpful vs. safe)

Reward Model Training

Converting preferences to reward function

Process:

1. Collect preference pairs: (x, y_w, y_l)
2. Train model: $r(x, y_w) > r(x, y_l)$
3. Use Bradley-Terry model or similar

Loss function:

$$L = -\log \sigma(r(x, y_w) - r(x, y_l))$$

Result: Model that scores response quality

Constitutional AI

Anthropic's approach to AI alignment

Key idea: Define principles, not just preferences

1. Define constitution (principles like "be helpful", "be harmless")
2. AI critiques its own outputs against principles
3. AI revises based on self-critique
4. Human feedback on principles, not instances

Annotation role:

- Validate that principles are correct
- Check self-critique quality
- Identify edge cases

Direct Preference Optimization (DPO)

Skip the reward model

Traditional RLHF:
Preferences $\rightarrow$ Reward Model $\rightarrow$ RL Training

DPO:
Preferences $\rightarrow$ Direct LLM Training

Benefits:

- Simpler pipeline
- No reward model to train
- More stable training
- Same preference data requirements

Key insight: Preference data is the bottleneck, not the algorithm

Data Requirements for DPO

What you need:

- Prompts (from target distribution)
- Chosen responses (preferred)
- Rejected responses (dis-preferred)

Data format (Hugging Face):

- `prompt`: The input query
- `chosen`: Preferred response
- `rejected`: Dis-preferred response

Scale:

- 10K-100K pairs for good results
- Quality matters more than quantity
- Diverse prompts important

Annotation Challenges

Common issues in preference annotation:

Subjectivity:

- Different annotators have different preferences
- Cultural variation
- Personal style preferences

Biases:

- Position bias (prefer first/second)
- Length bias (prefer longer/shorter)
- Verbosity bias (more words = better?)

Fatigue:

- Annotation quality degrades over time
- Need breaks and quality checks

Best Practices

For preference annotation:

1. **Clear criteria:** Define what "better" means
2. **Randomize order:** Avoid position bias
3. **Multiple annotators:** 3+ per pair recommended
4. **Calibration:** Regular alignment sessions
5. **Quality control:** Monitor agreement over time
6. **Fair pay:** Preference annotation is cognitively demanding

Tools for Preference Annotation

Specialized platforms:

- **Argilla:** Built for RLHF data collection
- **Label Studio:** Customizable for comparison
- **Scale AI:** Commercial platform
- **Surge AI:** Managed workforce

Key features needed:

- Side-by-side response display
- Randomization of order
- Multiple response comparison
- Tie/skip options

Next Class: Safety & Red Teaming

Lecture 24 (Apr 22): Safety & Red Teaming Annotation

Topics:

- Red teaming and adversarial annotation
- Harmfulness and toxicity annotation
- Content moderation datasets
- Safety evaluation benchmarks
- Ethical considerations

Key Takeaways

1. **RLHF** aligns LLMs using human preference data
2. **Preferences are easier** to annotate than demonstrations
3. **Reward models** learn to score response quality
4. **Constitutional AI** uses principles instead of instance-level feedback
5. **DPO** simplifies training by skipping reward model
6. **Quality preference data** is the key bottleneck

Questions?

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Office Hours: Wednesdays 1-3pm, Volen 109

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