

Machine Learning

Machine Learning: Jordan Boyd-Graber University of Maryland

Policy Search

- Problem: often feature-based policies that work well aren't those that approximate V/Q best
- Solution: Find policies that maximize rewards rather than the value that predicts rewards
- Successful



Example: Imitation Learning

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- What if we diverge?

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- DAGGER: Dataset aggregation [Ross, Gordon & Bagnell, 2010]
- searn: Searching to Learn [Daumé & Marcu, 2006]

Applications of Imitation Learning

- Car driving
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Question Answering



Question Answering



• State: The words seen, opponent

Action: Buzz or wait

• Reward: Points

Why machine translation really hard is

- State: The words you've seen, output of machine translation system
- Action: Take translation, predict the verb
- **Reward**: Translation quality





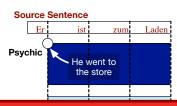










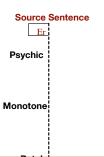


Good Translation

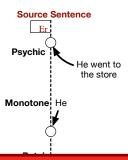
Bad Translation



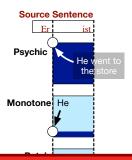




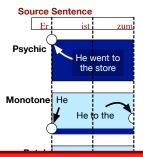




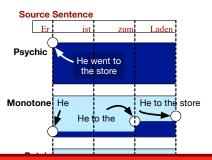




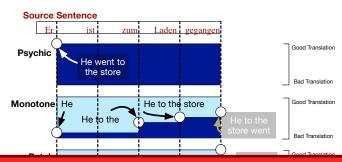


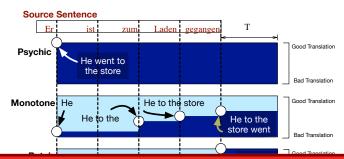


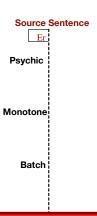




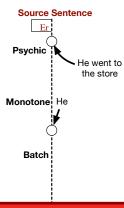




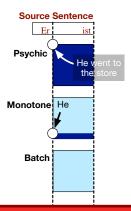




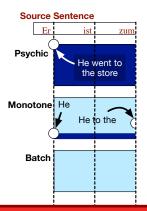




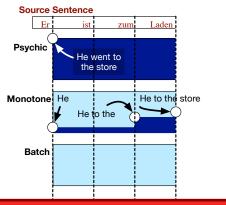




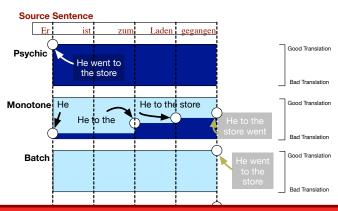


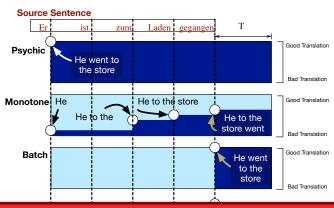


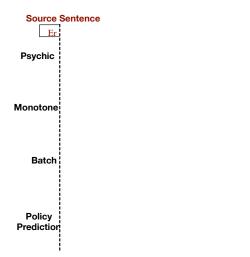




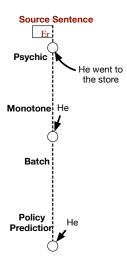




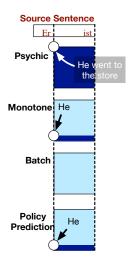




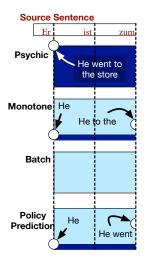




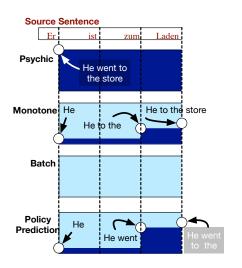




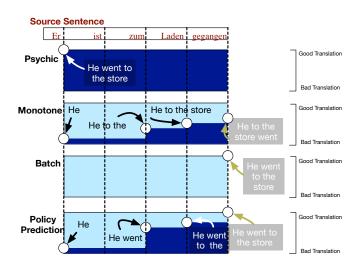


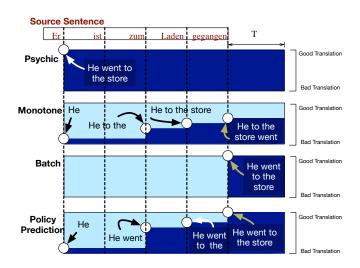


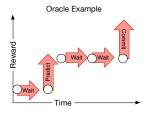


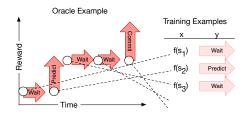


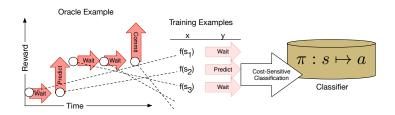


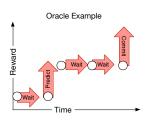


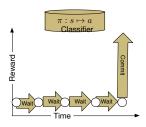


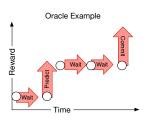


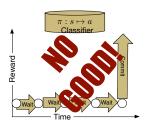


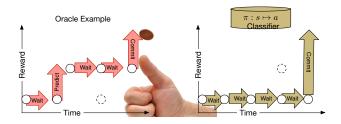


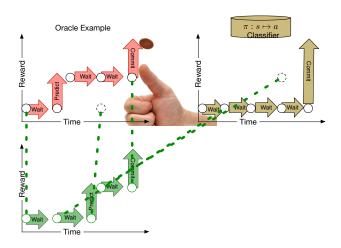


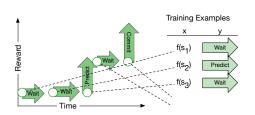


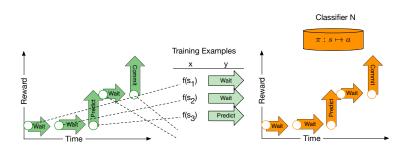












Recap

- Learning from examples: immitation learning
- Role of supervised machine learning
- Room for deep learning . . .