L06: Embeddings & RL

Text Representations and Sequential Decision Making

Methods and Algorithms

MSc Data Science

Spring 2026

Outline

Three zones: Introduction, Core Content (PMSP), and Wrap-Up

When All You Have Is Linear Algebra...

"You pour the data into this big pile of linear algebra, then collect the answers on the other side."

XKCD #1838 "Machine Learning" by Randall Munroe (CC BY-NC 2.5)

The Text Data Challenge

Financial text is everywhere—but machines cannot read

- Earnings calls, analyst reports, and news articles contain market-moving signals
- Text is unstructured: no rows, no columns, no obvious features
- We need to capture semantic meaning—"bullish" should be close to "positive outlook"

The core question: How do we convert words into numbers that preserve meaning?

Embeddings turn text into numbers that ML models can process

The Sequential Decision Challenge

Trading is not a one-shot prediction—it is a sequence of decisions

- A portfolio manager makes buy, sell, and hold decisions every day
- Each action has delayed consequences: today's trade affects next week's P&L
- The explore-vs-exploit dilemma: stick with what works or try something new?

The core question: How do we learn an optimal strategy from trial and error?

Reinforcement learning: learning from trial and error with delayed rewards

Why Banks and Asset Managers Care

Embedding Applications in Finance

- **Sentiment analysis:** Classify news as positive/negative for trading signals
- **Document similarity:** Find related filings, detect duplicate reports
- **Entity recognition:** Extract company names, tickers, and financial events

Reinforcement Learning Applications in Finance

- **Algorithmic trading:** Learn buy/sell/hold policies from market data
- **Portfolio rebalancing:** Optimize allocation over time with transaction costs
- **Optimal execution:** Minimize market impact when filling large orders

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Both techniques address real problems in quantitative finance and risk management

Learning Objectives

By the end of this lecture, you will be able to:

1. **Derive** the Skip-Gram objective and analyze the negative sampling approximation
2. **Evaluate** static vs. contextual embeddings for domain-specific NLP tasks (e.g., FinBERT)
3. **Analyze** the convergence properties of Q-learning and the role of the exploration–exploitation tradeoff
4. **Critique** RL-based trading strategies and their limitations (transaction costs, non-stationarity, overfitting)

Finance Application: Sentiment-driven trading signals and sequential portfolio optimization

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Bloom's taxonomy levels 4–5: Analyze, Evaluate, Derive, Critique

The Business Problem

Text Data: One-Hot Encoding Wastes Dimensions

- A vocabulary of 50,000 words $\Rightarrow$ 50,000-dimensional sparse vectors
- No notion of similarity: "bank" and "financial institution" are equally distant
- Embeddings compress words into dense vectors of 100–768 dimensions

Sequential Decisions: Delayed Reward Signals

- Supervised learning needs immediate labels; trading profit is realized days later
- The agent must learn which past actions led to eventual gains or losses
- RL explicitly models the credit-assignment problem via reward discounting

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Embeddings solve the text problem; RL solves the sequential decision problem

Key Equations

Embeddings — Skip-Gram Objective:

$$\max \sum_{t=1}^{T} \sum_{\substack{-c \le j \le c \\ j \neq 0}} \log p(w_{t+j} \mid w_t)$$

Cosine Similarity:

$$\text{sim}(u, v) = \frac{u \cdot v}{\|u\| \, \|v\|}$$

Example: $\cos(\text{“king”}, \text{“queen”}) = 0.85$ (very similar) vs. $\cos(\text{“king”}, \text{“car”}) = 0.12$ (unrelated).

Reinforcement Learning — Bellman Equation:

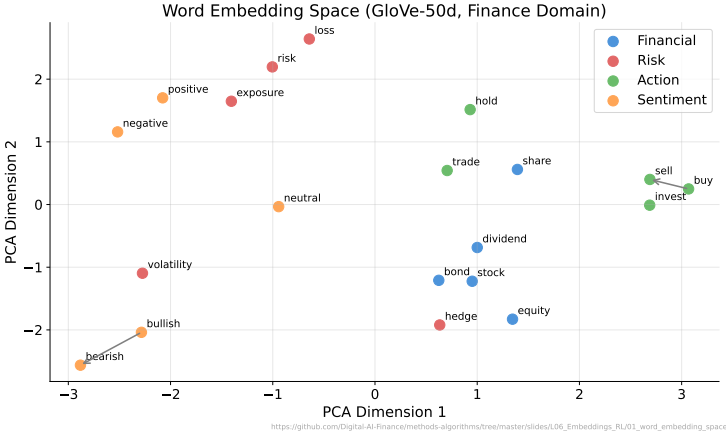
$$Q^*(s, a) = \mathbb{E}\big[r + \gamma \max_{a'} Q^*(s', a') \mid s, a\big]$$

TD Update (Q-Learning):

$$Q(s, a) \leftarrow Q(s, a) + \alpha\big[r + \gamma \max_{a'} Q(s', a') - Q(s, a)\big]$$

These four equations are the mathematical backbone of this lecture

Word Embedding Space



Similar words cluster together in embedding space

The Distributional Hypothesis

"You shall know a word by the company it keeps." — J.R. Firth (1957)

- Words appearing in similar contexts have similar meanings
- **Dense** vectors (100–300 dims) replace **sparse** one-hot vectors (50,000+ dims)
- **Word2Vec core idea:** Train a shallow neural network to predict context words from a target word (Skip-Gram) or vice versa (CBOW)

Word2Vec: the breakthrough that made word embeddings practical (Mikolov et al., 2013)

Static vs. Contextual Embeddings

Static Embeddings (Word2Vec, GloVe)

- One fixed vector per word, regardless of context
- "bank" always maps to the same point—whether river bank or investment bank

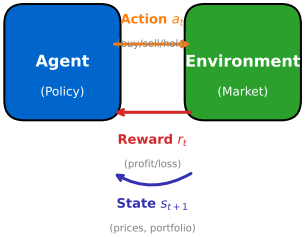
Contextual Embeddings (BERT, FinBERT)

- Different vector for each occurrence, depending on surrounding sentence
- "The **bank** approved the loan" vs. "We walked along the river **bank**"
- FinBERT: BERT fine-tuned on financial text—captures domain nuance

Static: one meaning per word. Contextual: meaning adapts to context.

RL: Agent-Environment Loop

Reinforcement Learning: Agent-Environment Interaction



https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L06_Embeddings_RL/03_rl_loop

Five core components:

- **Agent:** The decision maker (e.g., trading algorithm)
- **Environment:** The market or simulator
- **State:** Current portfolio, prices, indicators
- **Action:** Buy, sell, or hold
- **Reward:** P&L after each action

Agent takes actions, receives rewards, learns optimal policy

Q-Learning at a Glance

What is Q(s, a)?

- The expected total discounted reward from taking action a in state s, then acting optimally

How does the agent learn?

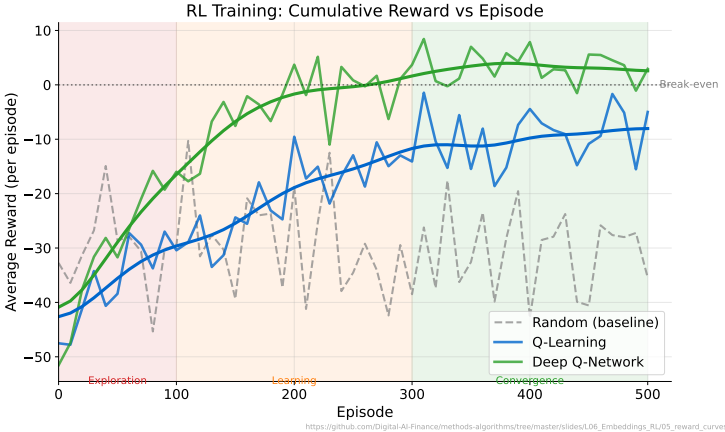
- **Update rule:** Blend old estimate with new evidence (controlled by learning rate α)
- **Target:** Immediate reward r plus discounted best future value $\gamma \max_{a'} Q(s', a')$
- Old and new are mixed: $Q_{\text{new}} = (1 - \alpha)\, Q_{\text{old}} + \alpha\, [\text{target}]$

Exploration vs. Exploitation

- ϵ-greedy: with probability ϵ, choose a random action (explore); otherwise, choose the best known action (exploit)

Q-learning: the foundation of value-based reinforcement learning

Learning Progress



RL agents improve through exploration and exploitation over many episodes

Embeddings in Finance: Sentiment Analysis

Worked Example

- Input headline: "Fed signals aggressive rate hike amid inflation fears"
- Embed headline into a 768-dimensional vector using FinBERT
- Compute cosine similarity to positive/negative anchor phrases
- Classification: **Negative sentiment** (bearish for equities)

Why FinBERT?

- General BERT struggles with financial jargon ("hawkish", "dovish")
- FinBERT achieves 87% accuracy on financial sentiment (Araci, 2019)

Simplified example — real embeddings are 300–768 dimensions

RL in Finance: Trading Agents

Formulation

- **State:** Price history, technical indicators, current position
- **Action:** Buy, sell, hold (possibly with position sizing)
- **Reward:** Risk-adjusted return (e.g., Sharpe ratio per step)

Key Challenges

- **Non-stationarity:** Market regimes shift—policies trained on bull markets fail in crashes
- **Overfitting:** Agent memorizes historical patterns that do not repeat
- **Partial observability:** The agent never sees all relevant information

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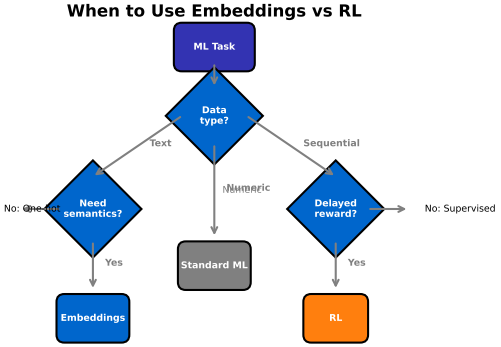
RL for trading is an active research area; not a solved problem

Embeddings vs. Reinforcement Learning

	Embeddings	**Reinforcement Learning**
Input	Text data (words, sentences, docs)	Sequential decisions with delayed feedback
Learns	Semantic representations (dense vectors)	Optimal policy (state $\rightarrow$ action mapping)
Finance Use	Sentiment analysis, document similarity	Trading strategies, portfolio optimization

Both transform complex inputs into learnable representations

Decision Framework



Embeddings: Text, categorical -> dense vectors (Word2Vec, BERT)

RL: Sequential decisions with delayed rewards (trading, games)

https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L06_Embeddings_RL/07_decision_flowchart

Embeddings for text, RL for sequential decisions with delayed rewards

Practical Tips

Embeddings

- Start with pre-trained models (Word2Vec, GloVe, or FinBERT)—training from scratch requires massive corpora
- Match the domain: financial text needs financial embeddings
- Visualize with t-SNE to sanity-check that clusters make sense

Reinforcement Learning

- Start simple: tabular Q-learning before DQN or policy gradient
- Design rewards carefully—reward shaping prevents sparse-signal problems
- Normalize states: RL is sensitive to feature scales

Both domains: start simple, iterate, validate thoroughly

Hands-on Exercise

Open the Colab Notebook

1. **Exercise 1:** Explore word embeddings with Word2Vec—find similar words and visualize clusters
2. **Exercise 2:** Implement basic Q-learning on a grid-world environment
3. **Exercise 3:** Apply RL to a simple trading environment and analyze the learned policy

Link: `https://colab.research.google.com/github/Digital-AI-Finance/methods-algorithms/blob/master/notebooks/L06_embeddings_rl.ipynb`

Notebooks available on the course GitHub page — see the L06 folder

Key Takeaways

Embeddings

- Words become dense vectors where proximity encodes semantic similarity
- Pre-trained models (Word2Vec, GloVe, FinBERT) give you a strong starting point

Reinforcement Learning

- An agent interacts with an environment, learning from rewards over time
- Q-learning and DQN provide practical algorithms for value-based control

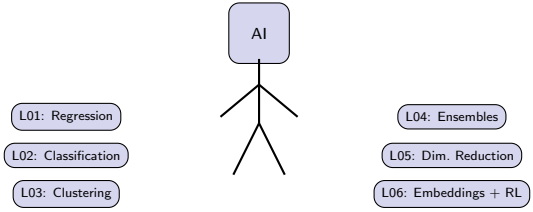
Finance Applications

- Embeddings power sentiment analysis, document search, and entity extraction
- RL enables algorithmic trading, portfolio rebalancing, and optimal execution

Key Insight: Both methods transform raw, complex inputs into structured representations that machines can learn from.

Course complete! Apply these methods in your capstone project

The Complete ML Toolkit



"Six lectures, one toolkit. Now go build something."
— Your Methods & Algorithms course

Course complete! Apply these methods in your group assignment and capstone project.

References

- Mikolov, T., Chen, K., Corrado, G. & Dean, J. (2013). *Efficient Estimation of Word Representations in Vector Space*. arXiv:1301.3781.
- Sutton, R.S. & Barto, A.G. (2018). *Reinforcement Learning: An Introduction*, 2nd ed. MIT Press. Free at `http://incompleteideas.net/book/the-book-2nd.html`
- Jurafsky, D. & Martin, J.H. (2024). *Speech and Language Processing*, 3rd ed. `https://web.stanford.edu/~jurafsky/slp3/`
- Araci, D. (2019). *FinBERT: Financial Sentiment Analysis with Pre-Trained Language Models*. arXiv:1908.10063.

Sutton & Barto: the definitive RL textbook (free at incompleteideas.net)