Chapter 6, "fThe Machine Learning Process,"

This chapter sets the stage for using machine learning (ML) models in trading by explaining the fundamental concepts and the typical steps involved in developing an ML solution. It's like learning how to build something – you need to understand what tools you have, how to use them, and follow a plan

1. How Machine Learning From Data Works

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At its heart, machine learning is about using computer programs (algorithms) that can **learn rules and patterns automatically from data**34. Think of it like teaching a computer by showing it many examples, rather than giving it step-by-step instructions for every possible situation4.

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The main goal is often to **build an analytical model** that can then perform a specific task, like making predictions or classifying things45.

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Once an algorithm is "trained" using a dataset, it can then be given new, unseen data to perform the task5. In the context of trading, this task is often predicting things about the market6....

Example: The sources mention previous research that used ML to predict if stocks on the Indian stock exchange would increase or decrease the next day6. This is an example of ML learning from historical stock data to make a future prediction.

2. The Challenge: Matching the Algorithm to the Task

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There's no single perfect ML algorithm that works best for every problem10. This is sometimes called the "no-free-lunch theorem"10.

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The challenge is choosing an algorithm that is suitable for the specific problem you want to solve and the data you have1011. An algorithm can only learn certain types of patterns, which is limited by its "hypothesis space"1213.

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If you pick an algorithm that's too simple, it might not be able to capture the complex patterns in your data (this is called **underfitting**)14.

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If you pick an algorithm that's too complex for the amount of data you have, it might learn patterns that are just random noise in the training data, and won't work well on new data (this is called **overfitting**)14.... Finding the right balance is key.

Example: The sources compare different ML models like SVM, LSTM, and Random Forest for predicting stock price movements919. They are chosen because they represent somewhat different ways of finding patterns20. An LSTM is good at finding patterns over time sequences, while a Random Forest combines multiple simpler models20.

3. Supervised Learning: Teaching by Example

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This is the most common type of ML21.

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It's called "supervised" because you use data that has the **correct answers, or labels**, to guide the learning process21. The algorithm learns by trying to predict these known answers21.

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Tasks in supervised learning fall into two main categories:

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Classification: Predicting a **category** or class (like "will the stock price go up or down?" - two categories)22. You can also have more than two categories (multiclass classification), like predicting if a stock belongs to the top 10% of performers, the bottom 10%, or somewhere in between22.

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Regression: Predicting a **continuous number** (like "what will the stock price be tomorrow?" or "what will the percentage return be?")22.

Example: The study in the sources uses supervised learning (specifically classification) to predict if a stock's price will increase or decrease6.... The training data includes historical stock data *and* the actual outcome (whether the price went up or down), which serves as the correct "label" for the model to learn from6....

4. Unsupervised Learning: Uncovering Useful Patterns

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Unlike supervised learning, this type of ML uses data that **does not have predefined labels or correct answers**2324.

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The goal is to find hidden structure, patterns, or groupings within the data on its own23.... It's like letting the algorithm explore the data freely24.

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Common tasks include:

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Clustering: Grouping similar data points together24....

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Dimensionality Reduction: Reducing the number of features or variables while trying to keep the most important information25.... This helps simplify complex data.

Example: Unsupervised learning could be used to group stocks based on their price movement patterns or risk characteristics, even if you don't have pre-defined categories for these groups2428. The sources mention using it to find "data-driven risk factors" from asset returns using PCA (Principal Component Analysis), which is a dimensionality reduction technique2932. It can also be used for "topic modeling" to find hidden themes in large amounts of financial news text28....

5. Reinforcement Learning: Learning by Trial and Error

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This involves an "agent" that learns to make decisions by **interacting with an environment**2....

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The agent takes actions in the environment and receives feedback in the form of **rewards** (for good actions) or penalties (for bad ones)2....

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The goal is for the agent to learn a strategy (called a "policy") that maximizes the total reward it receives over time2....

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This is seen as particularly suitable for algorithmic trading because trading is essentially making decisions (actions) in a dynamic, uncertain environment (the market) to achieve a goal (profit)2....

Example: A trading agent could be trained using reinforcement learning. It might take actions like "buy," "sell," or "hold" a stock39. It would receive rewards based on whether these actions lead to profit or loss39. The agent would learn over many trials which actions tend to lead to higher rewards in different market situations240.

6. The Machine Learning Workflow

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Building an ML solution isn't just about picking an algorithm; it's a process12. The sources outline a typical workflow1...:

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Define the problem: Clearly state what you want to achieve and how you'll measure success22....

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Collect and prepare data: Gather the necessary data, clean it, and format it correctly41.... This includes avoiding using information from the future that wouldn't have been available at the time ("look-ahead bias")45....

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Explore data and engineer features: Understand the data, visualize relationships, and create new, more informative inputs (features) for the model41....

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Select an ML algorithm: Choose a model suitable for your task and data50....

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Train, test, and tune the model: Train the algorithm on your data, evaluate how well it works, and adjust its settings (tune hyperparameters) to improve performance51.

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Use the model: Finally, deploy the trained model to make predictions or decisions to solve your problem51.

Example: The overall thesis described in sources6... follows this workflow: They defined the problem (predicting stock movement direction)9, collected historical stock data54, prepared it by calculating technical indicators and converting them to discrete values6..., selected different ML models (SVM, LSTM, RF)919, trained and tested them756, and then evaluated their results against a baseline756.

7. Basic Walkthrough: K-Nearest Neighbors (KNN)

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Chapter 6 uses KNN as a simple example to walk through parts of the workflow57.

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KNN can be used for both regression and classification57.

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It works by finding the 'k' training data points that are "nearest" to a new data point (often using distance measures like Euclidean distance)57.

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For classification, it predicts the class that is most common among those 'k' neighbors57. For regression, it might predict the average value of the neighbors57.

Example: The source mentions using a house price dataset to illustrate KNN51. While not a trading example *in this specific section*, imagine using KNN for a trading classification task: To predict if a stock will go up tomorrow, you find the 10 (k=10) historical days that are most similar to today based on your features (e.g.,

technical indicators). If 7 of those 10 similar days resulted in the stock price going up, KNN might predict "up" for tomorrow.

8. Framing the Problem: From Goals to Metrics

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This is the crucial first step4143. You need to be very clear about what you're trying to predict (e.g., a specific price vs. just the direction of movement)9.

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You also need to define how you'll measure if your model is doing a good job4143. These are your evaluation metrics58.

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For classification (like predicting up/down): Metrics include **accuracy** (percentage of correct predictions)1956, precision, recall, and the **F1-score** (which balances precision and recall)5659. A **confusion matrix** shows how many predictions were correct vs. incorrect for each class60.... ROC curves and AUC are also used to evaluate classifiers45.

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For regression (like predicting a price): Metrics often relate to the difference between the predicted and actual values63.

Example: The study measures the performance of its models using **accuracy** and **F1-score** to see how well they predicted the direction of stock price movements56. They also define their prediction task as predicting the *direction* of price movement, not the exact price9.

9. Collecting and Preparing the Data

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You need to get the data (like historical stock prices)4554.

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Data often isn't perfect, so it needs to be **cleaned** (e.g., fixing missing values, handling errors)6465.

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Data needs to be in the right format for the ML algorithm65. Time series data (like stock prices over time) requires special care to maintain the correct order4765.

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Crucially, you must avoid using future information in your training data that wouldn't have been known at the time of prediction. This is called "look-ahead bias" and will make your model seem better than it is, failing when used in the real world45....

Example: The study downloaded 10 years of historical stock prices (open, high, low, close, volume) from Yahoo Finance5466. They also used a method to convert continuous data into discrete values6.... Data preprocessing is a key step mentioned in source64.

10. Exploring, Extracting, and Engineering Features

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Before modeling, it's helpful to understand your data using visualizations (like charts) and statistics49.

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Feature Engineering is the process of creating new, more informative input variables (features) from the raw data44.... This is often one of the most important steps for success6768.

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In trading, these features are often called **alpha factors** because they are designed to predict returns ("alpha")69.... They can be based on historical prices, volume, or other relevant data5572. Domain knowledge is very helpful here6773.

Example: The study used "technical indicators" calculated from historical stock prices as features6.... Technical indicators are like formulas applied to price and volume data to generate signals about potential future movements72. Examples include MACD, Williams %R, and Stochastic Oscillator55.

11. Selecting an ML Algorithm

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Based on your problem (classification/regression) and the nature of your data, you choose one or more ML algorithms to try5052.

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Different algorithms make different assumptions about the relationships in the data52.

Example: The study chose SVM, LSTM, and Random Forest models to compare their performance on the stock prediction task919.

12. Design and Tune the Model

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Once you select an algorithm, you need to design its architecture and set its configuration options, called **hyperparameters**5074. These aren't learned from the data directly but are set *before* training (like the number of trees in a Random Forest or the number of layers in a neural network)60.

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You then **train** the model using your prepared data50.

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A major challenge is managing the underfitting/overfitting trade-off1415. **Regularization** techniques help prevent overfitting74....

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You need to **tune** the hyperparameters to find the settings that give the best performance on new data5074.

Example: The study tuned the hyperparameters for their SVM, LSTM, and Random Forest models6078. This involved adjusting settings like the number of estimators for Random Forest or the layers and dropout for LSTM60.

13. How to Select a Model Using Cross-Validation

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Since the goal is for the model to work well on *new* data, you need a reliable way to estimate its performance beyond the data it was trained on79. This is where **cross-validation** comes in7980.

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Cross-validation involves splitting your available data into multiple subsets47. You train the model on some subsets and test it on others it hasn't seen79.

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This is especially tricky with time series data (like stock prices) because the order matters, and you can't use future data to train for past predictions (that would be look-ahead bias again)47.... Special methods like **time-series cross-validation** ensure that the training data always comes from *before* the test data8283.

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A common practice is to hold out a completely separate "test set" at the very end that the model never sees during tuning, for a final, unbiased evaluation74.

Example: The study used a variation of k-fold cross-validation during training78. They used the first 'k' parts of the data for training and the next part for validation78. The final comparison of models was made on a held-out "test set" which was the last year of data78. This helps estimate how well the models would perform on data they haven't seen before.

14. Parameter Tuning with Scikit-learn

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Chapter 6 mentions tools like Scikit-learn, a popular Python library for ML7884, which provides ways to automate the process of trying different hyperparameters and finding the best ones using cross-validation (like GridSearchCV)84....

Example: The study used Scikit-learn for implementing classifiers and tuning hyperparameters using a random search approach based on accuracy on the validation set78.

In summary, Chapter 6 lays the groundwork for applying machine learning by explaining the core ideas (supervised vs. unsupervised vs. reinforcement learning), the common steps involved in building an ML model, and important challenges like overfitting and how to evaluate performance reliably using techniques like cross-validation, especially considering the unique nature of financial time series data.