Lesson 36: Overfitting Prevention

Data Science with Python – BSc Course

Data Science Program

BSc Course

45 Minutes

Previously on L35...

We learned how networks train. But what if training goes **TOO well**?

L35 taught learning. L36 teaches when to STOP learning.

The Suspicious 99%

Scenario: Your model gets 99% accuracy on training data but 60% on new data. The CEO wants to deploy it tomorrow. What do you tell them?

After this lesson, you will be able to:

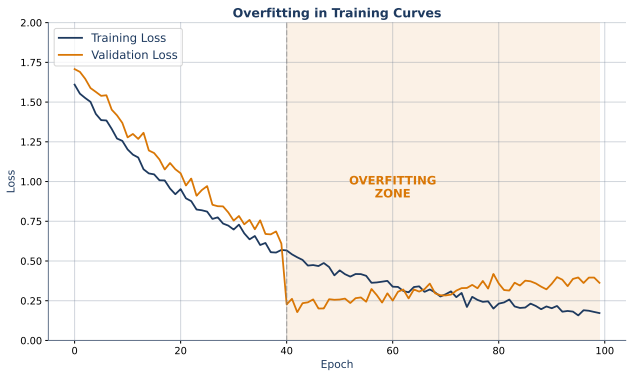
- Recognize overfitting in learning curves
- Apply dropout to prevent co-adaptation
- Use early stopping to halt at the right time
- Apply L2 regularization to control weight magnitude

Is 99% training accuracy always good news?

Overfitting: When Perfect Is Bad

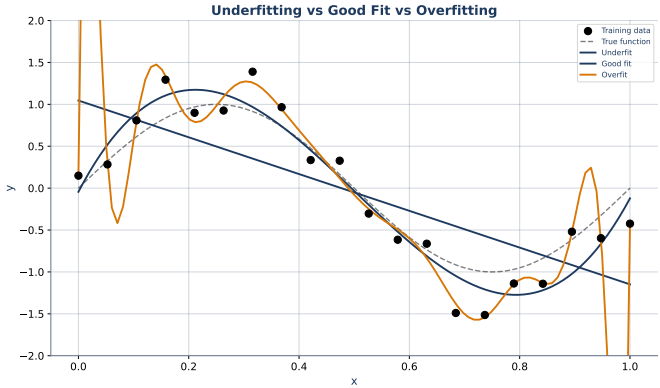
The model is MEMORIZING the training data instead of learning general patterns.

Like a student who memorizes answers but can't solve new problems.



Overfitting = memorizing noise instead of learning signal

Underfitting, Good Fit, Overfitting



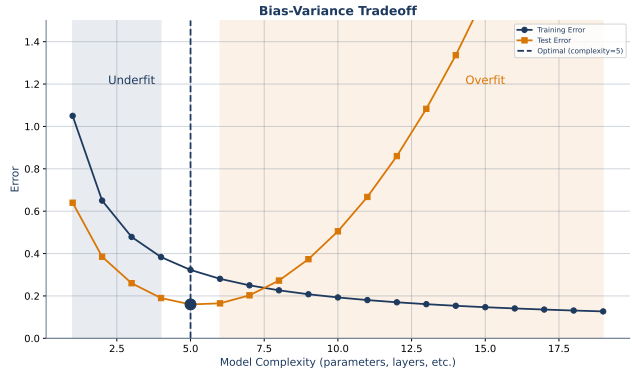
Too simple (underfitting) — Just right (good fit) — Too complex (overfitting).

The Goldilocks zone: complex enough to learn, simple enough to generalize

Bias-Variance: The Fundamental Tradeoff

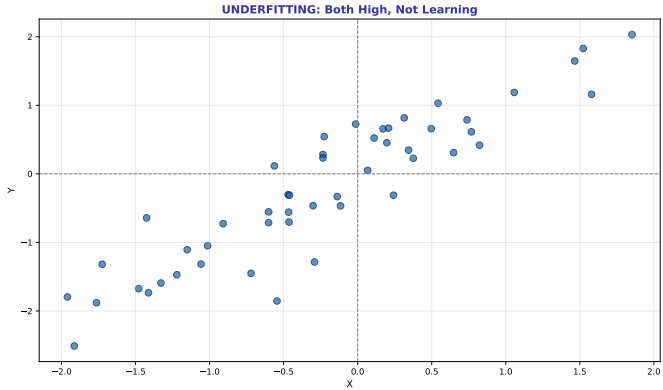
High bias = underfitting. **High variance** = overfitting.

The sweet spot is in the middle.



Three weapons ahead: Dropout, Early Stopping, L2 Regularization

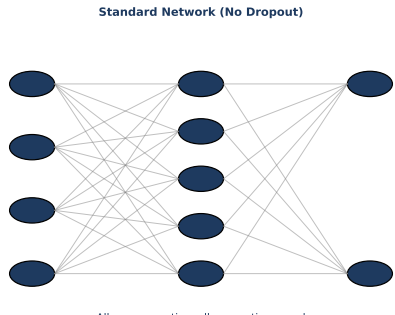
Underfitting: Both Losses High



Underfitting: model too simple or needs more training

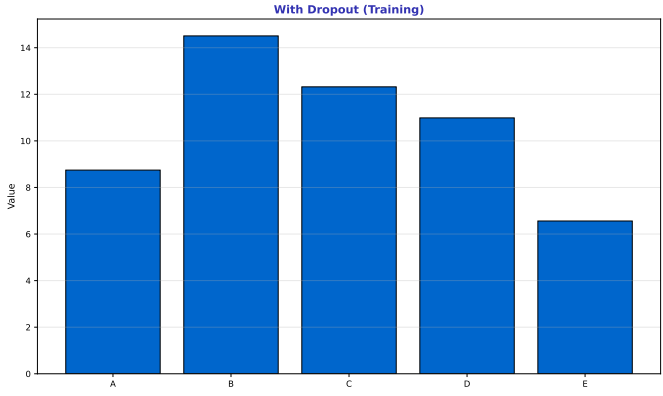
Weapon 1: Dropout

During training, randomly set some neurons to zero. Each batch sees a DIFFERENT sub-network.
Like studying with random pages missing—you learn the core concepts, not specific page numbers.



Dropout forces the network to learn redundant, robust representations

Dropout in Action



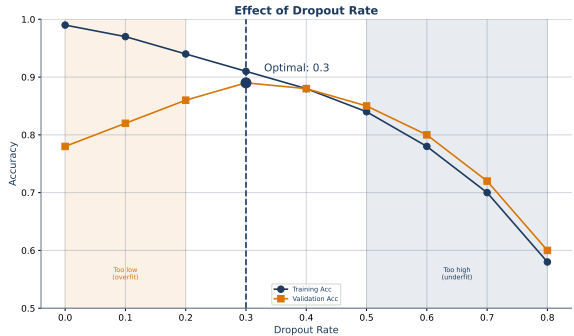
Different neurons dropped each batch—the network can't rely on any single path. It MUST learn robust features.

Each training step uses a different thinned network

How Much Dropout?

Typical rates: 0.2–0.5 for hidden layers.

Keras: `Dropout(0.3)` between Dense layers. During INFERENCE, all neurons active—dropout only during training.



Keras handles train/inference modes automatically

Dropout Syntax

Keras Sequential with Dropout:

- `Dense(128, activation='relu', input_shape=(n_features,))`
- `Dropout(0.3)` — drop 30% of neurons
- `Dense(64, activation='relu')`
- `Dropout(0.3)`
- `Dense(1, activation='sigmoid')` — no dropout on output

Automatic Behavior:

- Training: Dropout ACTIVE (neurons dropped)
- Inference: Dropout INACTIVE (all neurons used)

Common pattern: Dense → Dropout → Dense → Dropout

Dropout Best Practices

Recommended Rates:

Layer	Rate
After input	0.0–0.2
Hidden (small net)	0.2–0.3
Hidden (large net)	0.3–0.5
Before output	0.0–0.2

Use MORE when: Large model, small dataset, seeing large gap

Use LESS when: Small model, large dataset, model underfitting

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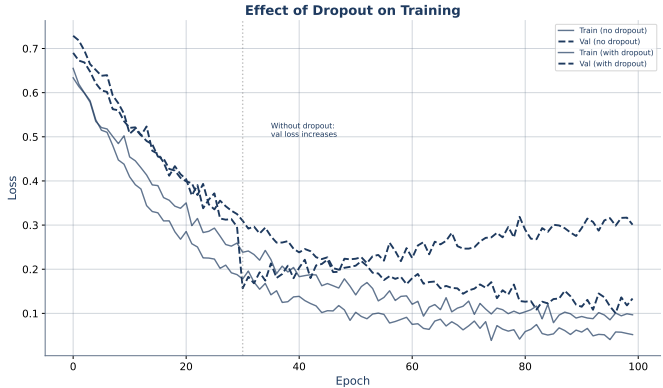
Start with 0.2, increase if overfitting persists

Dropout's Effect on Curves



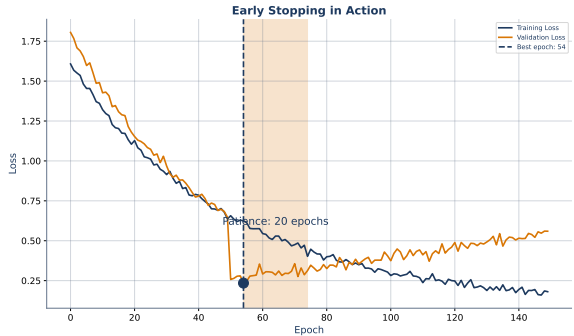
With dropout: training is slower but validation improves. The gap closes. You trade training speed for generalization. Always a good trade.

Slower training + better generalization = exactly what we want

Weapon 2: Early Stopping

Set epochs high (500), but STOP when validation loss stops improving.

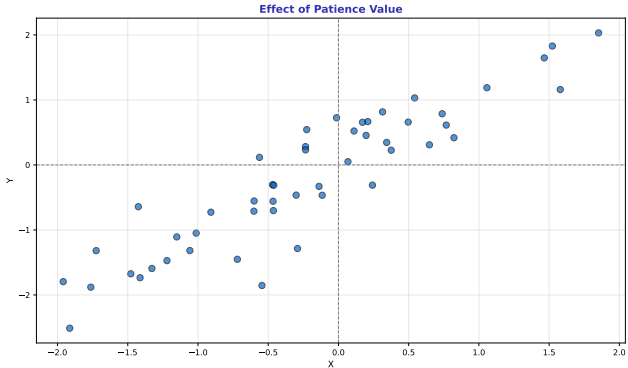
`EarlyStopping(patience=20, restore_best_weights=True)`



Best model = valley of the validation curve, not the last epoch

Patience: How Long to Wait?

Low patience = stops too early. **High patience** = waits too long.



10–30 is typical. Always use `restore_best_weights=True`.

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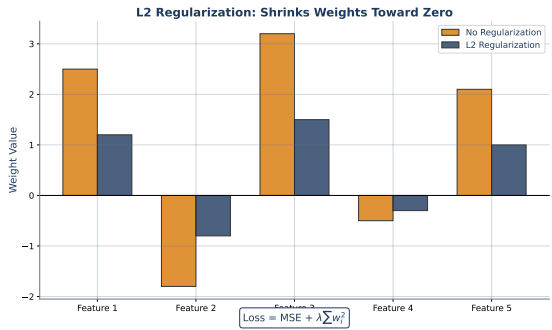
patience=20 is a safe starting point for most problems

Weapon 3: L2 Regularization

Add penalty for large weights to loss.

Keras: `kernel_regularizer=l2(0.001)`



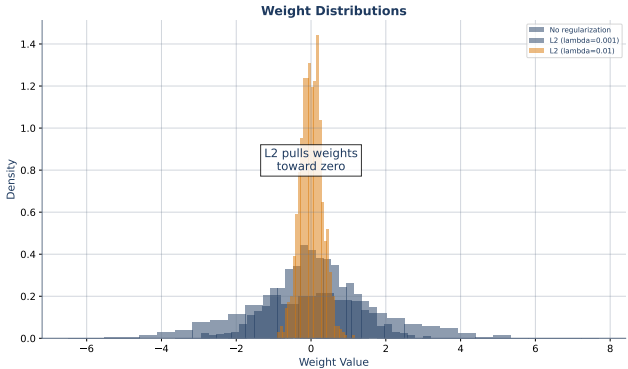
Same idea as Ridge from L22—large weights = too much faith in one feature.

L2 in neural networks = Ridge regression for deep learning

L2 Effect on Weights

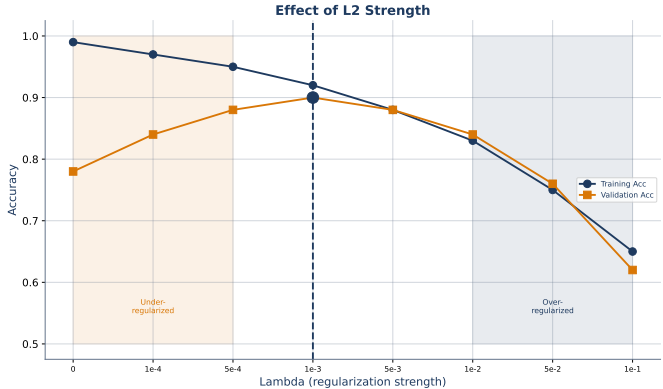
Without L2: weights spread out, some extreme.

With L2: concentrated near zero.



Smaller weights → simpler model → better generalization

Effect of L2 Strength



Higher lambda = stronger regularization. Typical: 1e-4 to 1e-2

L2 Keras Implementation

Per-Layer Regularization:

```
Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.001))
```

Common Lambda Values:

- 0.0001 (1e-4): Light regularization
- 0.001 (1e-3): Medium (good starting point)
- 0.01 (1e-2): Strong regularization

Elastic Net (L1+L2):

```
kernel_regularizer=regularizers.l1_l2(l1=0.001, l2=0.001)
```

Tip: Usually only regularize kernel (weights), not bias

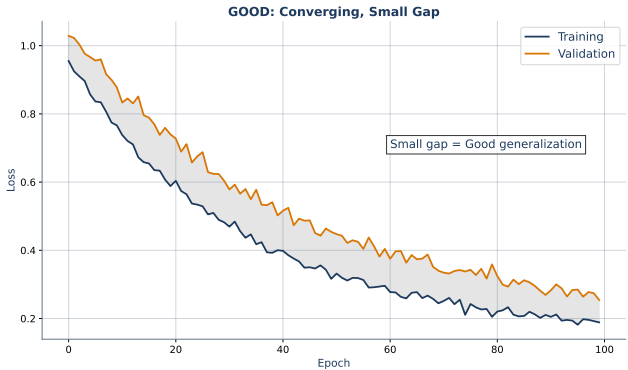
Apply regularizer to each Dense layer's kernel

Diagnostic Guide: Reading Learning Curves

Both high, flat Underfitting Fix: add layers/neurons	**Train low, val high** Overfitting Fix: dropout/early stop/L2
Both low, small gap Good Fit! Done – maybe fine-tune	**Both noisy** Bad LR or data Fix: lower LR, larger batch

Print this guide. You will use it every time you train a neural network.

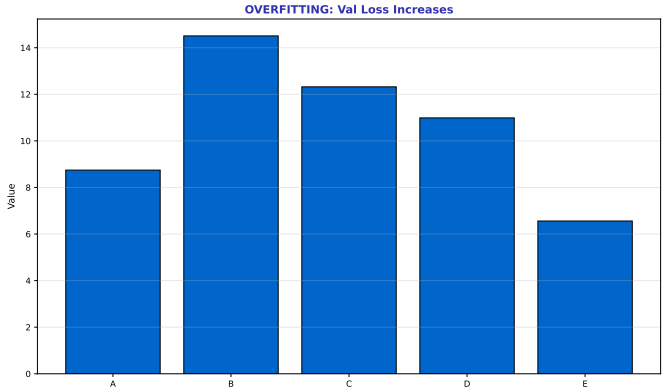
Good Training: Converging, Small Gap



This is what you're LOOKING for: both curves converge, small gap.

Goal: train and validation curves converge to similar low values

Discovery: What's Wrong Here?



What's happening? Which weapon(s) would you use? How can you tell it's overfitting and not underfitting?

Diagnose first, then prescribe. Which weapons would you deploy? (Pause 15s)

The Complete Keras Recipe

Put ALL weapons together in one model:

`Dense(64, 'relu')` → `Dropout(0.3)` → `Dense(32, 'relu')` → `Dropout(0.2)` → `Dense(1, 'sigmoid')`

Compile: `optimizer='adam', loss='binary_crossentropy'`

Callbacks:

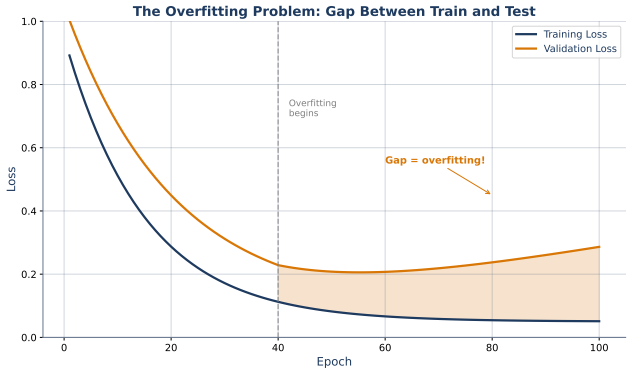
- `EarlyStopping(patience=20, restore_best_weights=True)`
- `ReduceLROnPlateau(patience=10, factor=0.5)`

Set `epochs=500` and let callbacks decide when to stop.

The recipe: dropout layers + early stopping callback + L2 optional

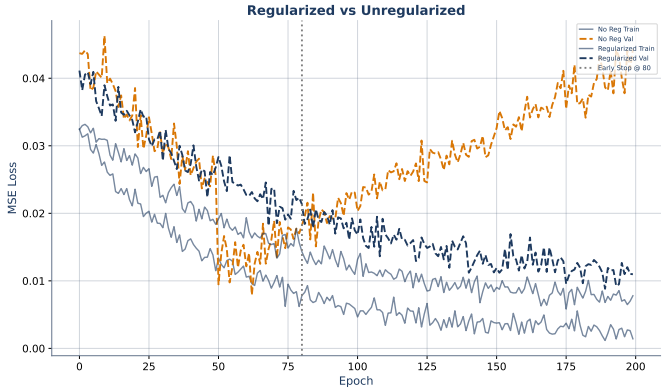
Finance: Fitting to Noise

Financial data is the HARDEST case for overfitting: noisy, non-stationary, limited samples. Regularization isn't optional—it's mandatory.



Financial ML mantra: regularize aggressively, validate relentlessly

Regularized vs Unregularized



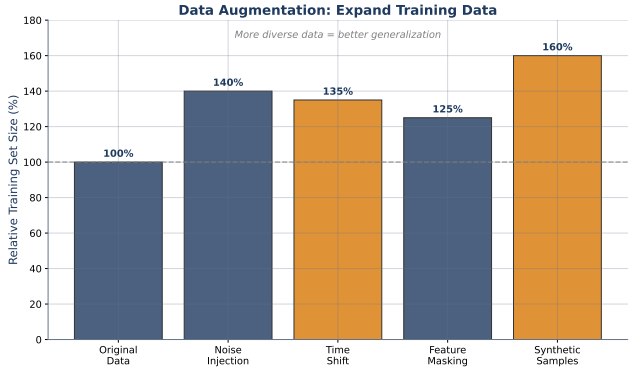
Dropout + early stopping + small network = your finance ML starter kit.

Simpler models often outperform complex ones on financial data

Data Augmentation Concept

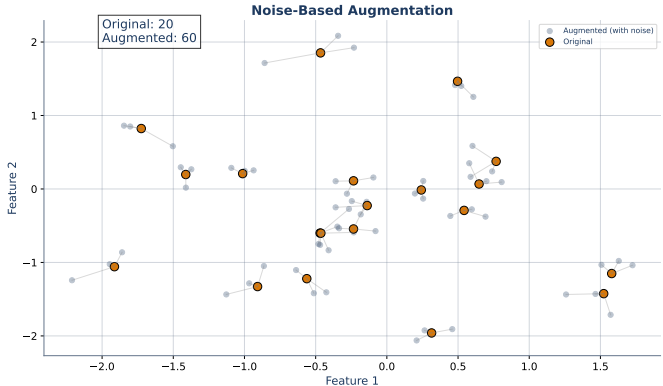
Creating More Training Data

- For images: rotate, flip, crop, adjust brightness
- For time series: add noise, time warping



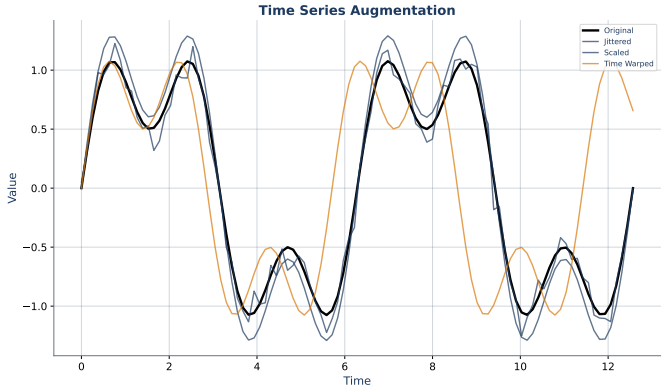
More diverse training data = better generalization

Noise-Based Augmentation



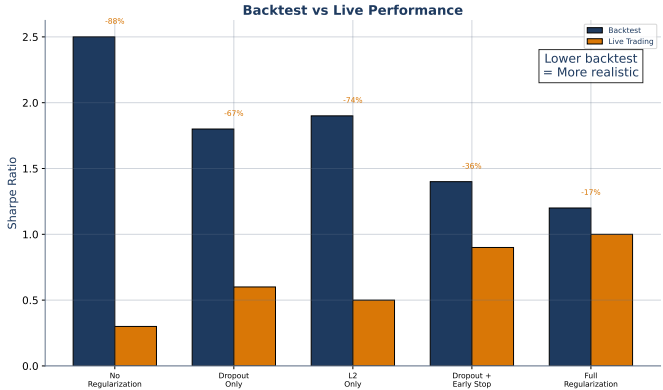
Add Gaussian noise to create variations of training samples

Time Series Augmentation



Time warping, magnitude scaling, window slicing for sequences

Backtest vs Live Performance



The ultimate test: does regularization help in live trading?

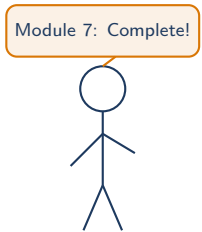
Hands-On Exercise (25 min)

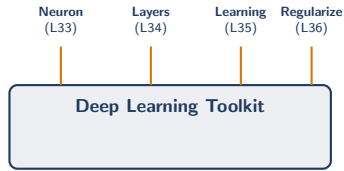
Task: Compare Regularization Techniques

1. Create overfit-prone dataset (200 samples, 50 features)
2. Train baseline MLP—observe overfitting in curves
3. Add Dropout(0.5)—compare curves
4. Add EarlyStopping—when does it stop?
5. Compare test accuracy across all variants in a table

Extension: Try combining dropout + L2 + early stopping

Module 7 Complete: Your Deep Learning Toolkit





Always check your validation loss!

Four lessons, one complete toolkit. You're ready for deep learning.

Key Takeaways

1. **Overfitting** = memorizing noise, not learning patterns
2. **Weapon 1: Dropout**—random neuron removal during training
3. **Weapon 2: Early stopping**—stop at the valley of val loss
4. **Weapon 3: L2**—penalize extreme weights (Ridge for neural networks)
5. **Finance:** regularize aggressively—noisy data demands it

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Three weapons, one goal: close the gap between train and validation

What's Next: Module 8 — Teaching Machines to Read

Neural networks process numbers. But finance is full of TEXT: earnings calls, analyst reports, news headlines.

Module 8 teaches machines to read.

L37: Text Preprocessing—turning words into numbers.

Next module: NLP—from text to predictions