

Episode 6: Metrics, Pipelines & Hyperparameter Tuning

Building ML Workflows You Can Trust

AI & ML: From Theory to Practice

Matthew Care 2026



What You'll Learn

By the end of this episode, you will understand:

- Why **accuracy** is **misleading** for unbalanced datasets
- How to use the **confusion matrix** to understand model errors
- **Precision, Recall, F1, and MCC** — what each metric captures
- How **Pipelines** automate data preparation and prevent data leakage
- The difference between **parameters** and **hyperparameters**
- How **intelligent tuning** finds the best model configuration
- How **ensembles** combine models for better predictions

Why Accuracy Fails

The Accuracy Paradox

The Problem with Accuracy

Accuracy = percentage of correct predictions. Sounds reasonable, right?

But consider this scenario — a fraud detection system:

Model	Accuracy	What It Actually Does
Model A	99%	Predicts "no fraud" for everything. Catches zero frauds.
Model B	95%	Actually detects 80 out of 100 fraud cases.

The paradox: The model with *lower* accuracy is clearly more useful! Accuracy alone is misleading when one class dominates.

A fire alarm that never goes off is "correct" 99.99% of the time — but it's useless.

When Can You Trust Accuracy?

Class Balance	Accuracy Reliable?
Balanced (50/50)	Yes
Slightly imbalanced (60/40)	Mostly
Moderately imbalanced (75/25)	Caution
Highly imbalanced (95/5)	No
Extremely imbalanced (99/1)	Definitely not

Rule of thumb: If the largest class makes up more than ~70% of the data, be sceptical of accuracy alone.

Most real-world problems have some degree of imbalance. We need better metrics.

Better Ways to Measure

The Confusion Matrix and Beyond

The Confusion Matrix

A 2×2 table of prediction outcomes:

	Predicted: Positive	Predicted: Negative
Actual: Positive	True Positive (TP)	False Negative (FN)
Actual: Negative	False Positive (FP)	True Negative (TN)

TP: Correctly predicted positive

TN: Correctly predicted negative

FP: Incorrectly predicted positive (**Type I error**)

FN: Incorrectly predicted negative (**Type II error**)

All classification metrics are built from these four numbers.

Understanding the Two Types of Error

False Positive (FP)

Type I Error — "False Alarm"

Predicted positive, but actually negative

- Flagging a legitimate transaction as fraud
- Diagnosing a disease in a healthy person
- Marking a real email as spam

False Negative (FN)

Type II Error — "Missed Detection"

Predicted negative, but actually positive

- Missing an actual fraud case
- Failing to detect a real disease
- Letting spam through to your inbox

The key question: In your application, which error is more costly?

In cancer screening, **missing a disease (FN)** is far worse than a false alarm (FP). In spam filtering, **deleting a real email (FP)** is worse than letting spam through (FN)

Precision: "How Trustworthy Are Positive Predictions?"

$$\text{Precision} = \frac{\text{True Positives}}{\text{All Positive Predictions}} = \frac{TP}{TP + FP}$$

"When the model says positive, how often is it right?"

- **High precision** → Few false alarms
- When you predict something is positive, you can trust that prediction

Precision matters when false alarms are costly:

- Don't delete real emails (spam filter)
- Don't freeze legitimate bank accounts (fraud detection)
- Don't raise unnecessary panic (alert systems)

A precise archer hits the target consistently — but might not choose to shoot at every target.

Recall: "How Complete Is Our Detection?"

$$\text{Recall} = \frac{\text{True Positives}}{\text{All Actual Positives}} = \frac{TP}{TP + FN}$$

"Of all the actual positive cases, how many did we find?"

- High recall → Few missed detections
- We're catching most of the positive cases

Recall matters when missing positives is dangerous:

- Don't miss cancer in a screening test
- Don't fail to detect a security threat
- Don't miss a relevant legal document in discovery

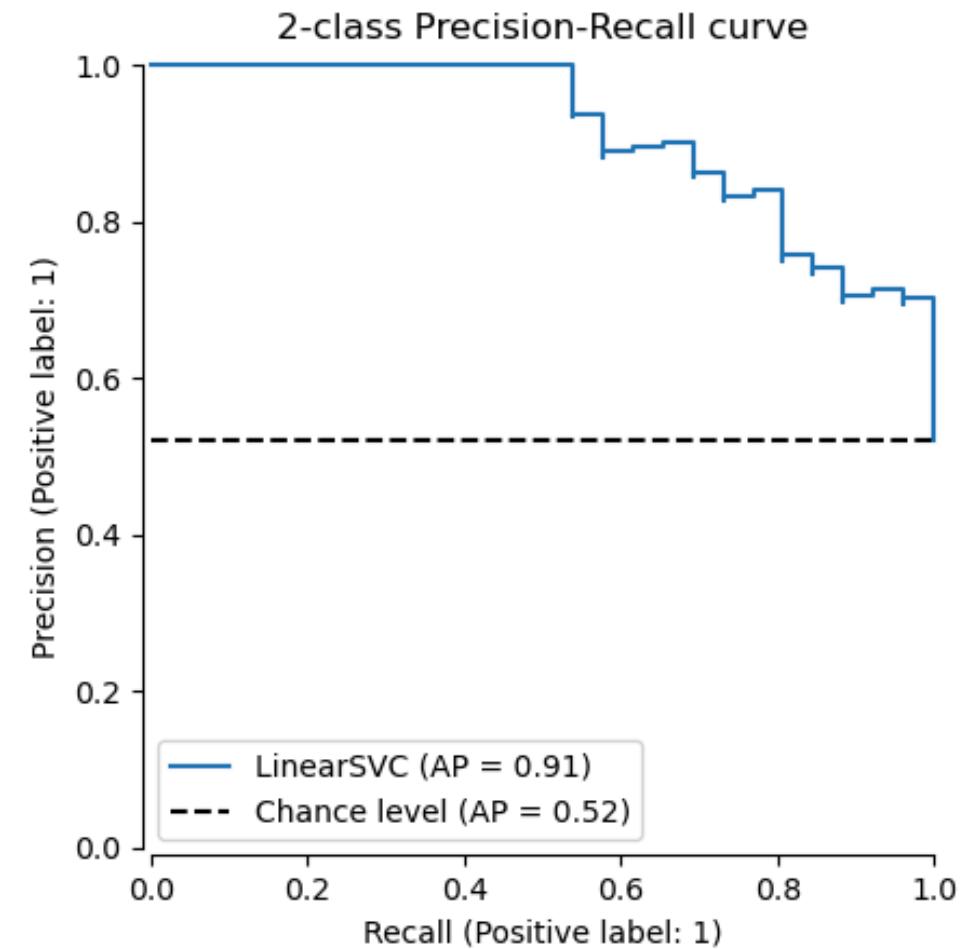
A thorough detective finds every clue — but might also investigate some false leads.



The Precision-Recall Trade-off

You usually can't maximise both. Improving one tends to worsen the other. The right balance depends on the costs of each type of error in your application.

An airport security system set very sensitively (high recall) catches every threat but also flags many innocent passengers (low precision). Dialled down, it's faster but might miss something...



Which Should You Prioritise?

Application	Priority	Reason
Email spam filter	Precision	Don't delete important emails
Cancer screening	Recall	Don't miss cancer cases
Search engine results	Precision	Top results should be relevant
Legal document review	Recall	Must find all relevant documents
Fraud detection	Depends	Balance false alarms vs missed fraud

Ask yourself: What's the real-world cost of a false positive compared to a false negative?

F1 Score: Balancing Precision and Recall

When you need a single number that balances both:

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Key property: F1 is high **only when both** precision and recall are high.

Precision	Recall	F1 Score
0.90	0.90	0.90
0.90	0.50	0.64
0.90	0.10	0.18

F1 penalises imbalance. You can't get a good F1 score by being great at one thing but terrible at the other.

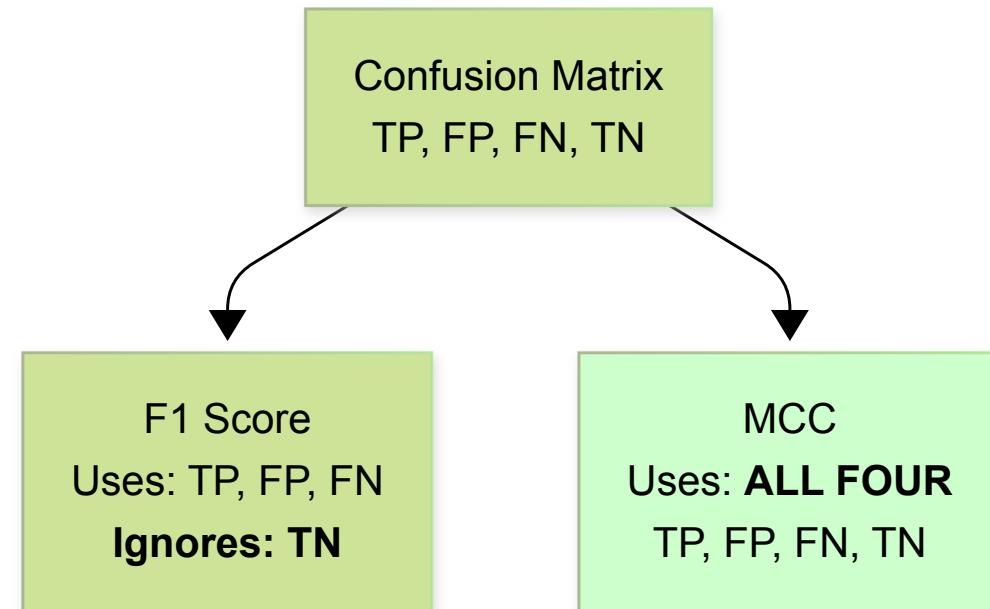


F1's Limitation: It Ignores True Negatives

F1 only uses TP, FP, and FN — it completely ignores TN.

This means F1 doesn't reward the model for correctly identifying negatives, e.g. a patient is disease free, a transaction isn't fraudulent etc.

For a truly balanced view of model performance, we need a metric that considers all four cells.



MCC: The Gold Standard for Imbalanced Data

Matthews Correlation Coefficient uses all four confusion matrix cells:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Score	Meaning
+1	Perfect predictions
0	No better than random guessing
-1	Perfectly wrong predictions

Critical advantage: A model that always predicts the majority class gets **MCC = 0**, while accuracy makes it look respectable (e.g., 76%). MCC correctly reveals it has no predictive power.

Comparing Metrics Side by Side

Same census income data, same useless "always predict majority" model:

Metric	"Always Predict ≤\$50K"	Actual Trained Model
Accuracy	76% (<i>looks okay!</i>)	83%
F1 (minority class)	0%	58%
MCC	0.00 (<i>correctly shows no value</i>)	0.52

Recommendation: Use **MCC** as your primary metric for imbalanced classification. Supplement with precision/recall for interpretability.

MCC is the truth-teller among metrics. It can't be fooled by class imbalance.

Choosing the Right Metric: Summary

Situation	Recommended Metrics
Balanced classes	Accuracy, F1, MCC (<i>all similar</i>)
Moderate imbalance	MCC , Balanced Accuracy, F1
Severe imbalance	MCC , per-class F1, PR AUC
False positives costly	Precision, Specificity
False negatives costly	Recall, Sensitivity
Need to rank predictions	ROC AUC, PR AUC

When in doubt, **MCC is the safest default**. It's honest regardless of class distribution.



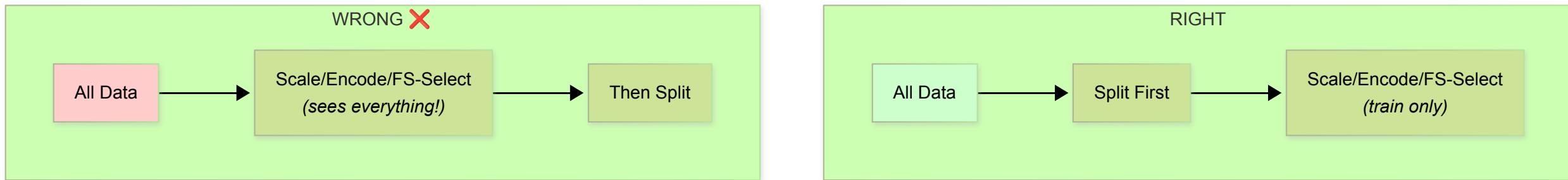
Building Reliable Workflows

Pipelines: Automating and Protecting Your Process

The Data Leakage Problem (Revisited)

From Episode 5: Never let test data influence training.

But this is surprisingly easy to get wrong:



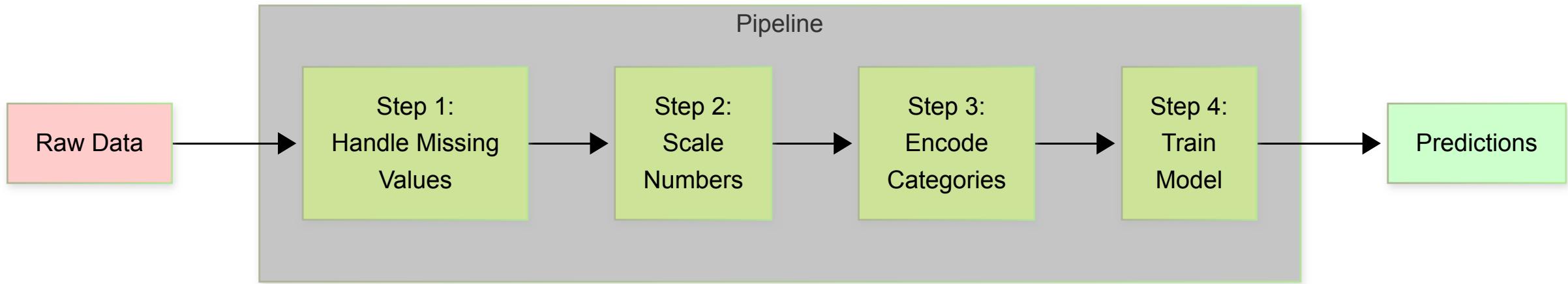
Doing this correctly during cross-validation (where you split multiple times) is **tedious and error-prone** if done manually.

This is where Pipelines come in — they automate correct methodology.

Easy to add additional functionality (e.g. over/under-sampling, feature-subsetting etc.)

What is a Pipeline?

A Pipeline chains all steps — preparation and modelling — into a single automated workflow:



The Pipeline automatically ensures:

- Each step is fitted on **training data only**
- The same transformations are applied consistently to new data (not learned again)
- No data leakage — even during cross-validation

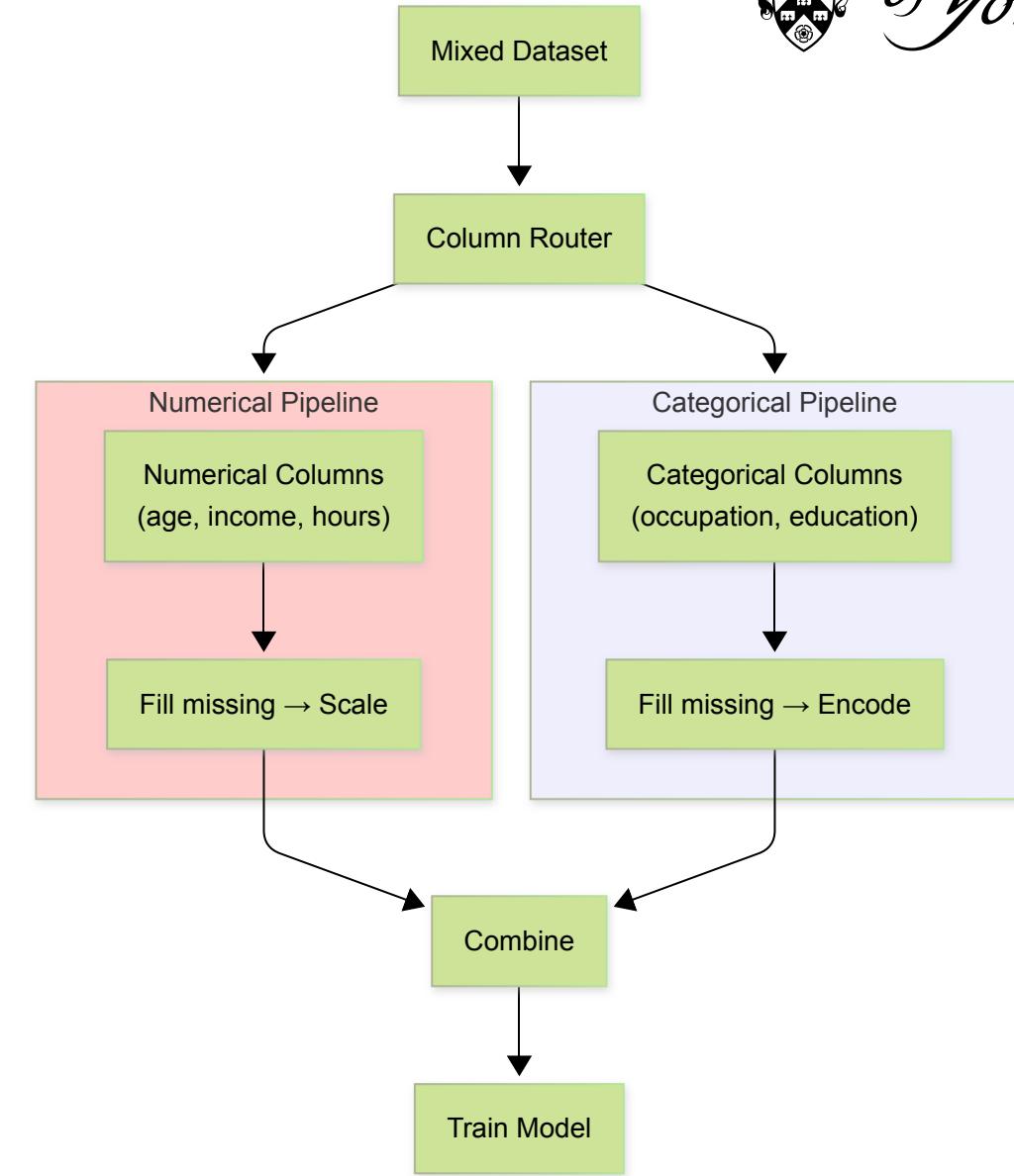
Think of it as an assembly line where each station does its job in the right order, every time, without mistakes.

Different Columns Need Different Treatment

Real datasets have mixed types — each needs its own preparation:

Pipelines handle this routing automatically — you specify which columns get which treatment, and the system manages the rest.

Handled via [Sklearn ColumnTransformer](#)



Pipeline Benefits

Correctness

- **No data leakage** — automatic isolation
- Consistent preprocessing every time
- Proper fit/transform separation

Convenience

- Single object to save and deploy
- Works with all evaluation tools
- Easy to experiment with different configurations

Best practice: Always use pipelines. They prevent subtle bugs that can silently invalidate your results.

A pipeline is like a standard operating procedure in a lab — it ensures every experiment follows the same rigorous protocol, regardless of who runs it.

Making Models Better

Hyperparameter Tuning

Parameters vs Hyperparameters

Parameters

Learned automatically during training

- Model discovers these from data
- Examples: coefficients, weights, split points

Like the specific skills a student develops through studying

Hyperparameters

Set by the user before training (external to learning)

- Control how the model learns
- Examples: learning speed, model complexity, number of trees

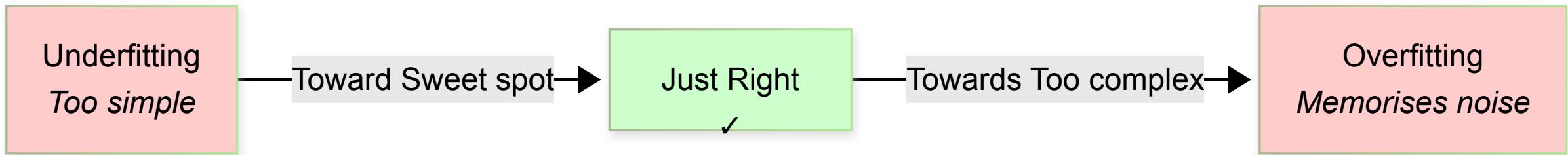
Like choosing class size, study hours, and teaching method

Hyperparameter tuning = systematically finding the best configuration settings for your model and data.

Why Tune Hyperparameters?

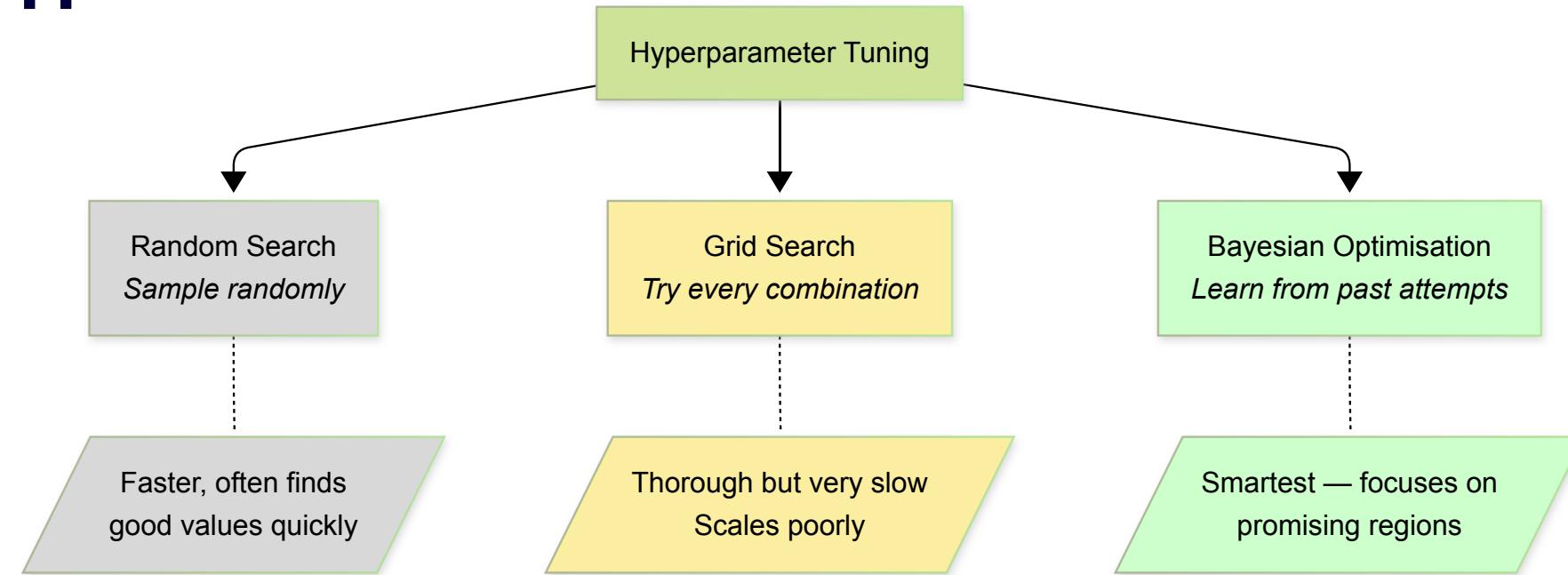
The same algorithm with different settings can produce very different results:

Setting	Effect
Model too simple	Underfitting — misses important patterns
Model too complex	Overfitting — memorises noise
Learning too fast	Unstable, jumps over good solutions
Learning too slow	Takes forever, may get stuck



Tuning is finding the Goldilocks zone — not too simple, not too complex, just right for your data.

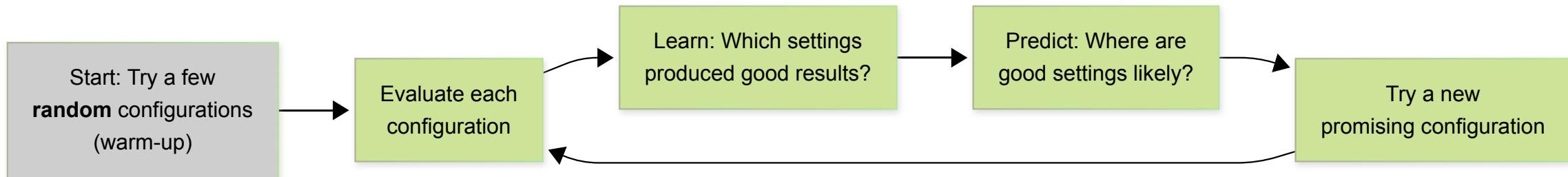
Tuning Approaches



Method	Trials Needed (4 settings, 5 options each)	Uses Past Results?
Grid Search	625 (tries all)	No
Random Search	~60–100	No
Bayesian (e.g. Optuna)	~30–50	Yes

Intelligent Optimisation: Learning From Experience

Bayesian optimisation (used by tools like Optuna) works like a smart scientist:



1. **Explore** randomly at first to understand the landscape
2. **Learn** which regions of the search space work well
3. **Exploit** that knowledge to focus on promising areas
4. **Repeat** — getting smarter with each attempt

Rather than blindly searching everywhere, it's like a prospector who learns where gold is likely and focuses their digging there.

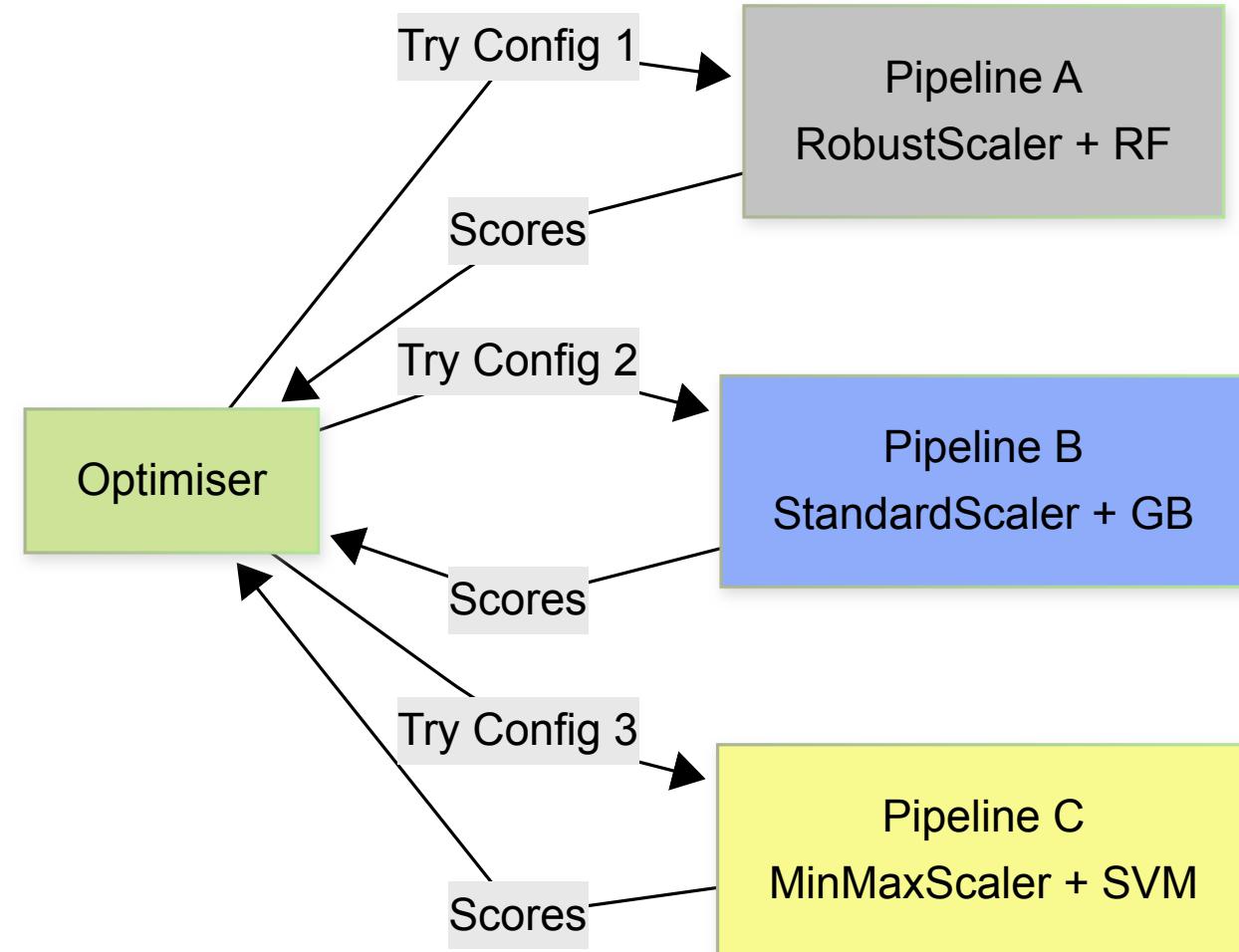
Tuning the Complete Pipeline

The real power: tuning everything together

Intelligent optimisation can simultaneously search for:

- The **best preprocessing** choices (which scaling method? Over/under-sampling, how to handle missing values?)
- The **best algorithm** (Random Forest? Gradient Boosting? SVM?)
- The **best hyperparameters** for the chosen algorithm

You're not just tuning one dial — you're tuning the entire instrument panel to find the best combination.



Fine-Tuning Results

Threshold Optimisation

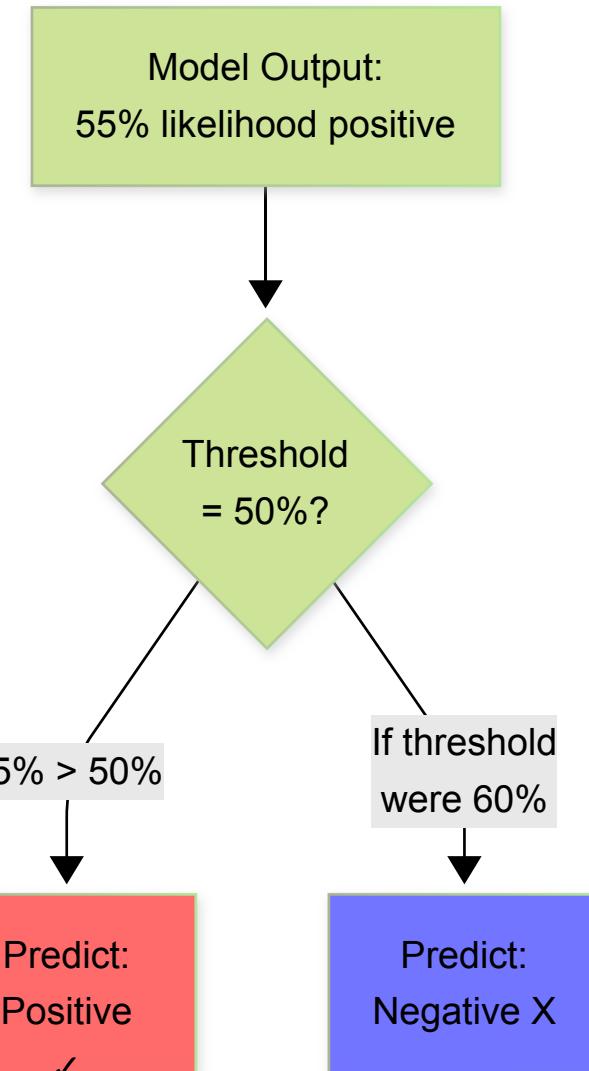
The Decision Threshold

Most models output a probability, then convert it to a prediction using a threshold:

The default threshold is 50%, but this assumes:

- Equal costs for both types of error
- Balanced class distribution
- Well-calibrated probabilities

These assumptions rarely hold in practice.



Adjusting the Threshold

Moving the threshold trades precision for recall:

Threshold	Effect
Lower (e.g., 30%)	More positive predictions → higher recall , but more false alarms
Default (50%)	Balanced starting point
Higher (e.g., 70%)	Fewer positive predictions → higher precision , but more missed cases

Optimise the threshold on validation data (not test data!) by searching for the value that maximises your chosen metric (e.g., MCC or F1).

Note: this needs an additional validation split (**not** done in CE1/CE2)

Combining Models

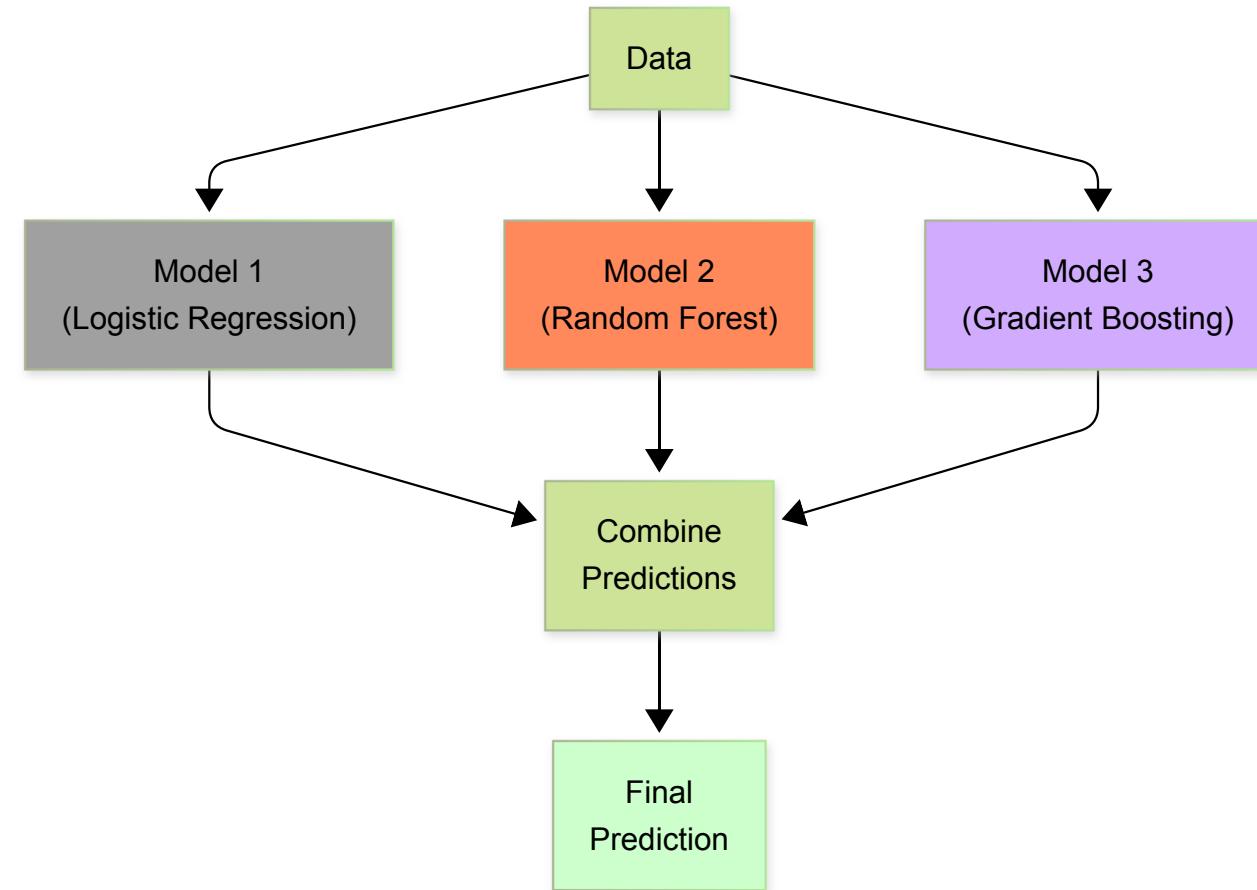
Ensemble Methods: The Wisdom of Crowds

Ensemble Methods: Why Combine Models?

Different models make different errors.
Combining them can average out mistakes.

A panel of doctors diagnosing a patient is likely to be more accurate than any single doctor. Each brings different expertise and perspectives.

Key requirement: models must be diverse — if they all make the same mistakes, combining them doesn't help.



Two Main Ensemble Approaches

Voting

Simple combination

- **Hard voting:** majority wins
- **Soft voting:** average the confidence scores

Like a committee voting on a decision

Simple, effective, easy to implement

Stacking

Learned combination

- Train a "meta-model" that learns *how* to best combine the base models
- The meta-model learns which base models to trust in which situations

like a senior consultant that knows which specialist is best for a particular problem, and combines their opinions into a final diagnosis

More powerful, but more complex

When Ensembles Help (and Don't)

Ensembles Help When:

- Base models are **strong but diverse**
- Models make **different types of errors**
- Sufficient data to train multiple models
- Slight accuracy improvement justifies the added complexity

Ensembles Don't Help When:

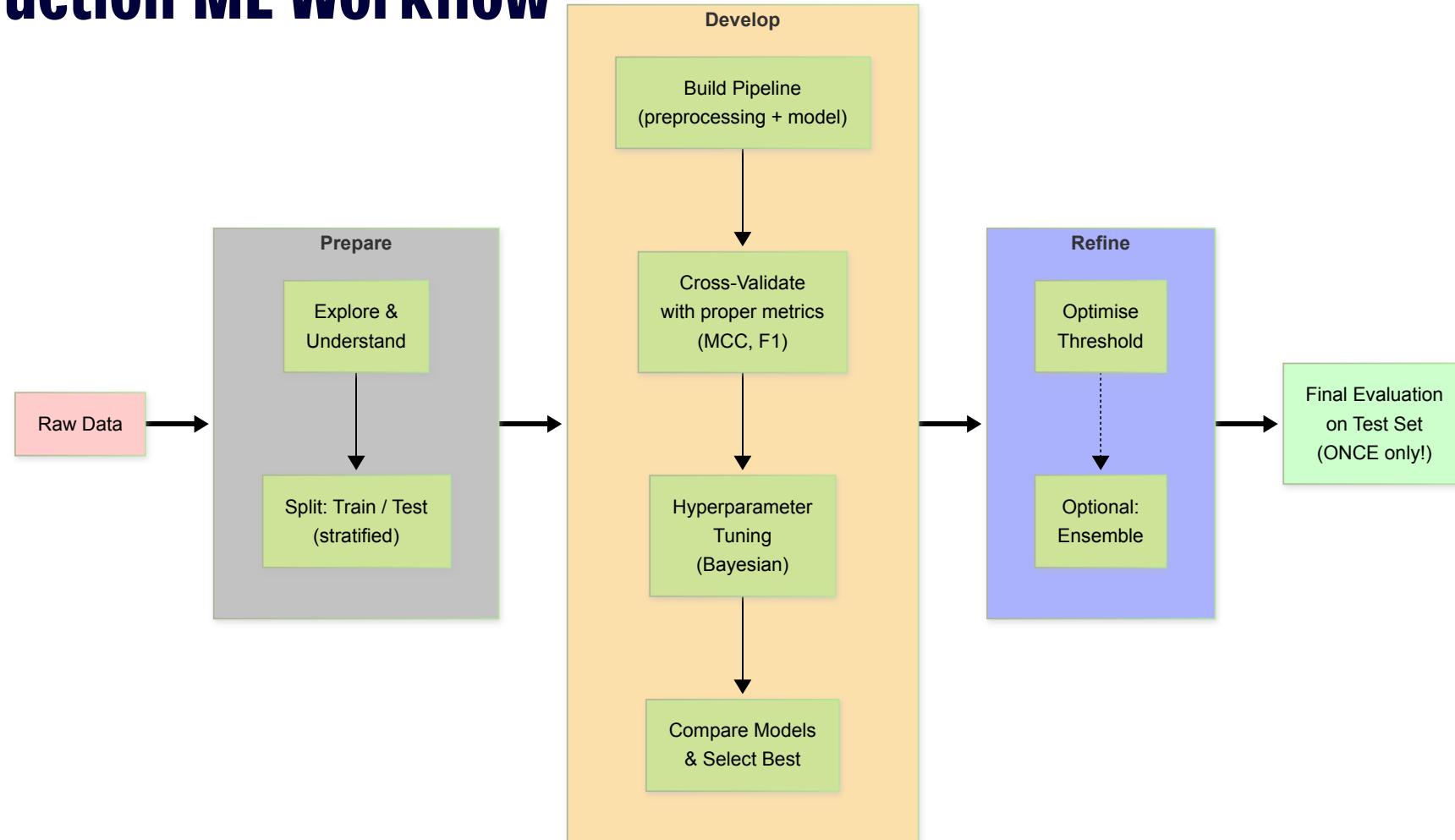
- All models are similar
- One model clearly dominates
- Interpretability is required
- Limited computation budget

Remember: Combining several weak models won't produce a strong one. Ensembles amplify diversity, not weakness.

Putting It All Together

The Complete ML Pipeline

The Production ML Workflow



Each step builds on the previous. Pipelines ensure correctness. Proper metrics ensure honesty. Tuning ensures optimal performance.



From CE1 to CE2

Aspect	Episode 5 (Basics)	Episode 6 (Production)
Data preparation	Manual, step - by - step	Automated Pipelines
Primary metric	Accuracy	MCC
Tuning	None	Bayesian optimisation (<i>Optuna</i>)
Class imbalance	Acknowledged	Addressed with metrics + resampling
Threshold	Default (0.5)	Optimised
Models	Single models	Ensembles of best models

Episode 5 teaches the fundamentals. Episode 6 teaches how to do them *properly and reliably*.



Key Takeaways

1. **Accuracy is misleading** for imbalanced data — it can make a useless model look good
2. The **confusion matrix** reveals what accuracy hides
3. **Precision** measures trustworthiness; **Recall** measures completeness
4. **MCC** is the most reliable single metric for imbalanced classification
5. **Pipelines** automate correct methodology and prevent data leakage
6. **Hyperparameters** control how models learn — tuning them matters
7. **Bayesian optimisation** finds good settings far more efficiently than brute force
8. **Threshold optimisation** and **ensembles** can further improve results

Questions Before CE2?

Up Next: Coding Exercise 2

You'll build a complete, production-quality ML pipeline!

- Expect it to take longer than CE1
- Read the detailed documentation in the notebook
- Experiment with different configurations
- Compare metrics to understand their behaviour

There are 3 versions of CE2: simple, advanced, expert - they build complexity from a functional starting point.

Remember: This is what real ML engineering looks like. Master these techniques and you can tackle any tabular ML problem.



Resources and Documentation

Metrics:

- [sklearn Metrics Guide](#)
- [MCC Wikipedia](#)

Pipelines:

- [sklearn Pipeline User Guide](#)
- [ColumnTransformer](#)

Optuna:

- [Optuna Documentation](#)
- [Optuna Tutorial](#)