

# Building Pipelines and Deploying Models with *targets*, *tidymodels*, and *vetiver* in R

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# Motivation

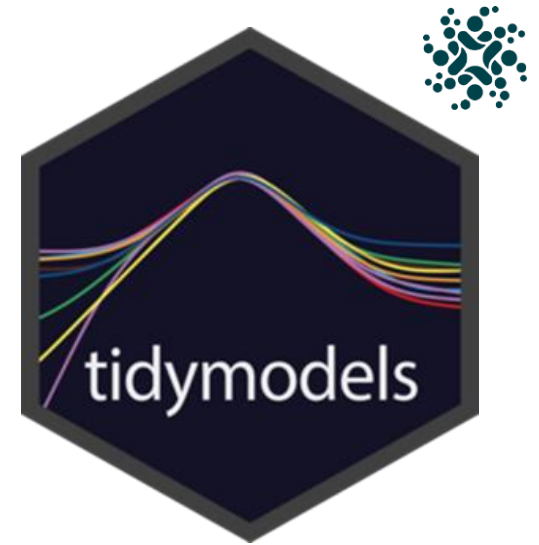


- Messy statistical and machine learning workflows
  - Ad-hoc scripts and notebooks
  - Not reproducible
  - Model deployment is an afterthought
- Solution: Tidy things up
  - Formalise workflows within pipelines
  - Standardise and modularise code into reusable components
  - Treat models as versioned and deployable S3 artifacts with documentation

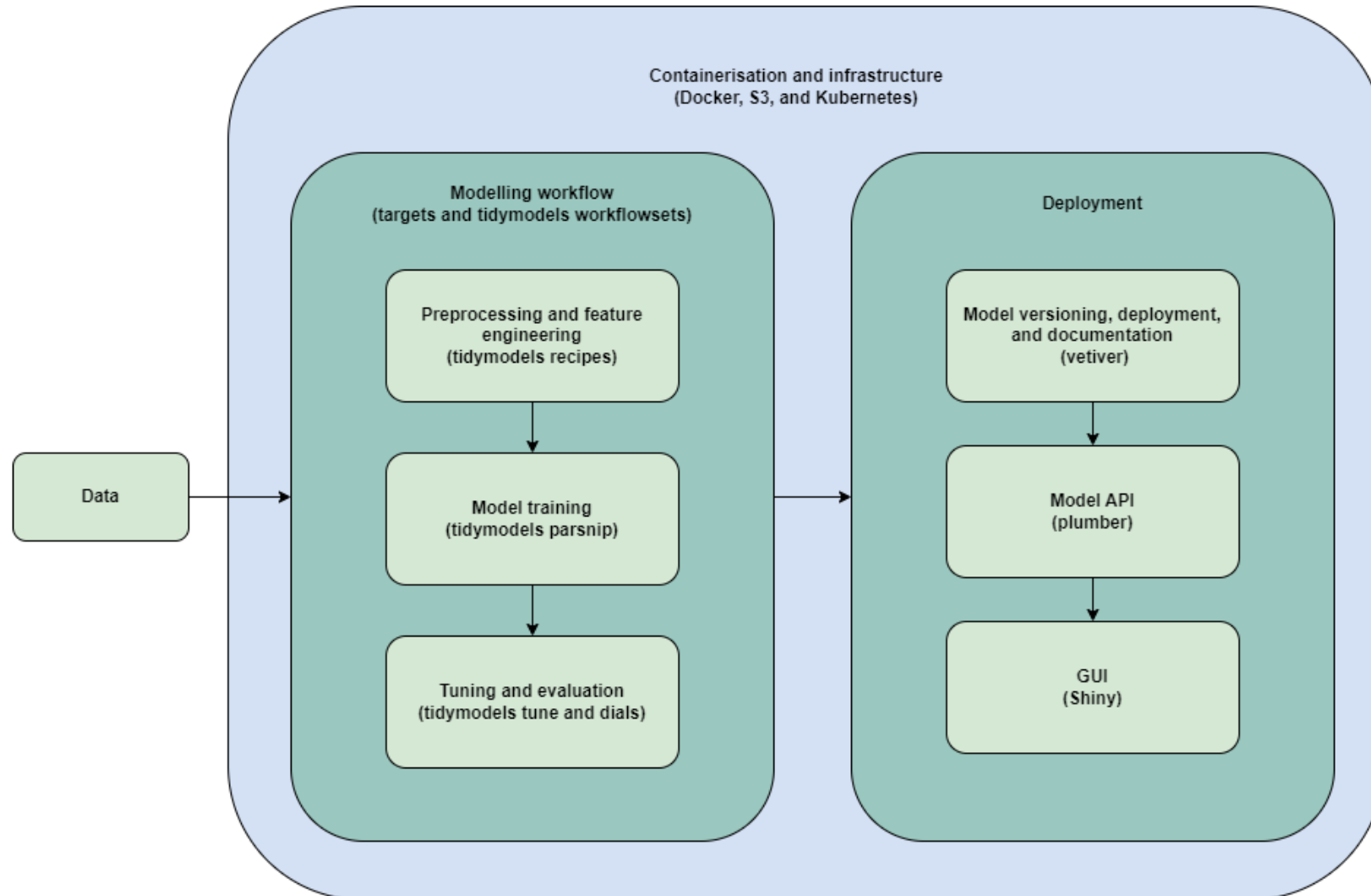


# DevOps and MLOps

- DevOps
  - Practices unifying software development and IT operations
  - Incorporating automation, infrastructure-as-code, and monitoring
  - Releasing stable code into production reliably and efficiently
- MLOps
  - Incorporates DevOps principles for machine learning (ML) systems
  - Ideas: Data & model versioning, reproducible pipelines, model deployment and cards
  - Reproducible, scalable, and trustworthy ML systems



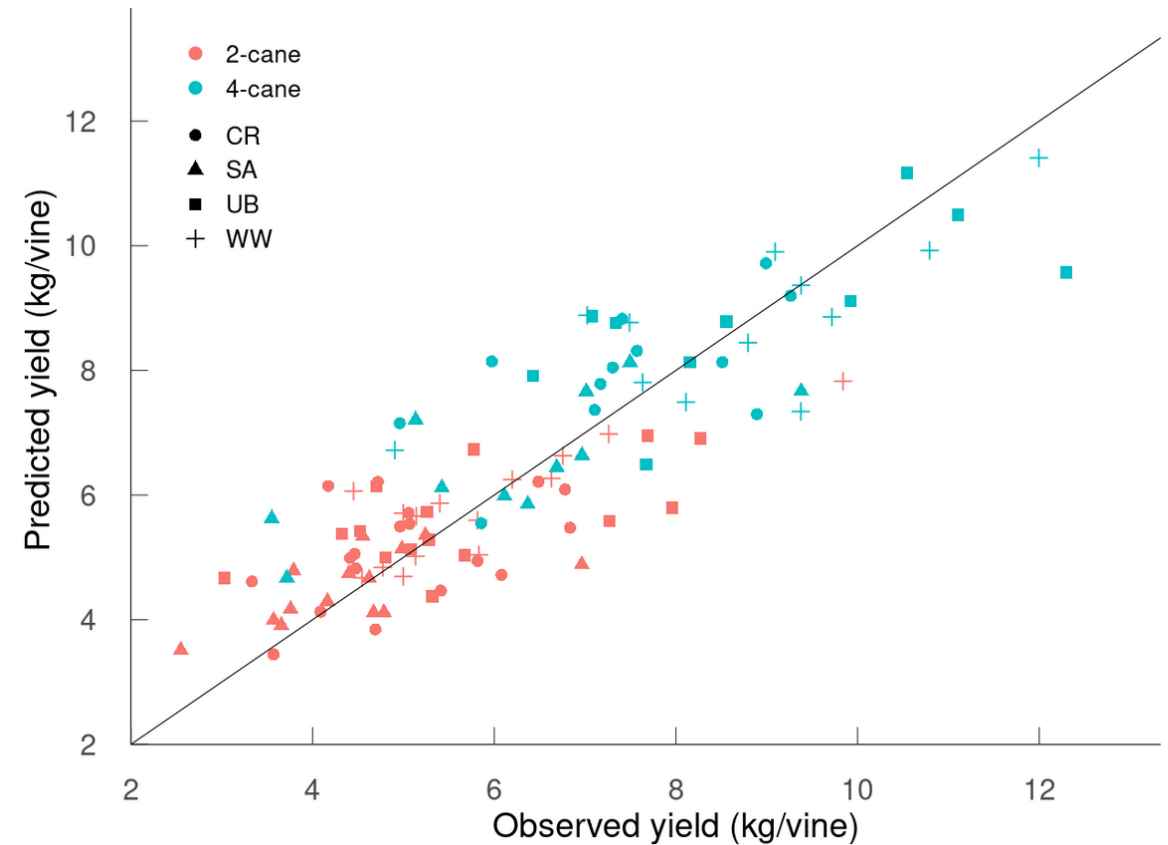
# MLOps Pipeline in R



# Case study: Grapevine yield prediction



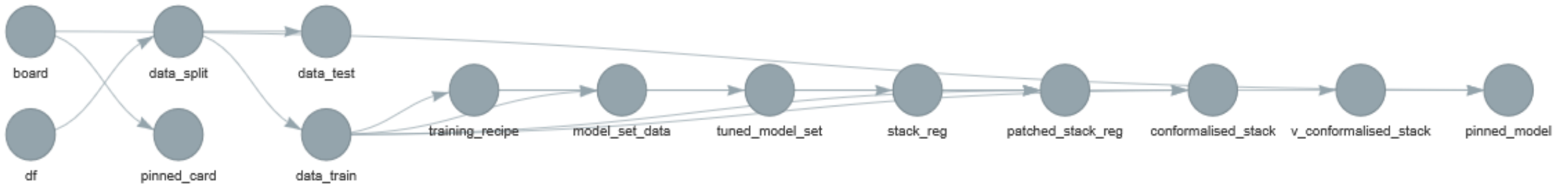
- Marlborough wine
- Two vs four cane pruning
- Four different vineyards
- Predicting yield from climatic conditions
- Predictive ML model: Conformalised stacking ensemble



# Reproducible targets pipelines



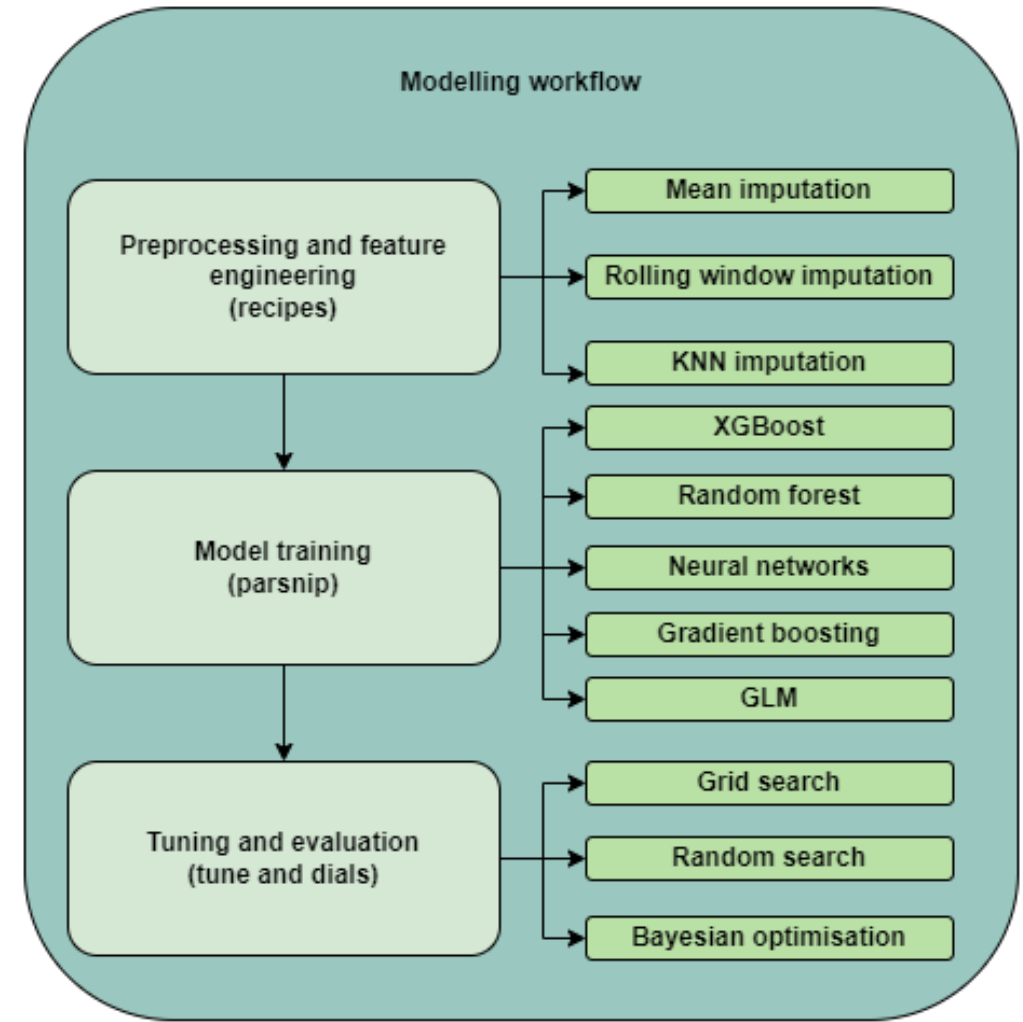
- Defines pipelines as a dependency graph (DAG)
- Automatically runs only what has changed
- Ensures end-to-end reproducibility, reducing manual reruns and "script chaos"
- Different backends via crew: Local; cloud (AWS, Google); and HPC (SLURM, SGE) execution environments



# tidymodels



- Combines preprocessing, modelling, and tuning in one workflow
- Consistent interface across model types
- Fair comparison and systematic tuning
- Supports reproducible modelling pipelines
- tidyverse successor to caret
  - caret: Monolithic package – one interface
  - tidymodels: Modular – swap and extend components

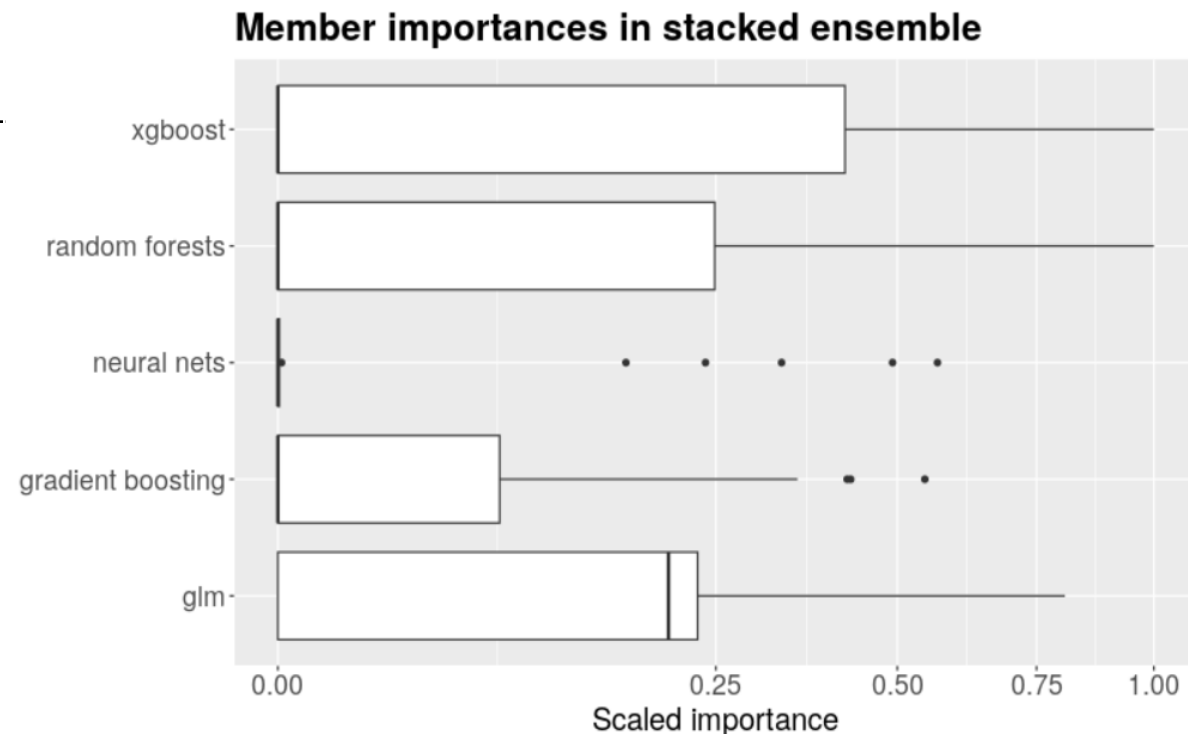


# workflowsets and stacking ensembles



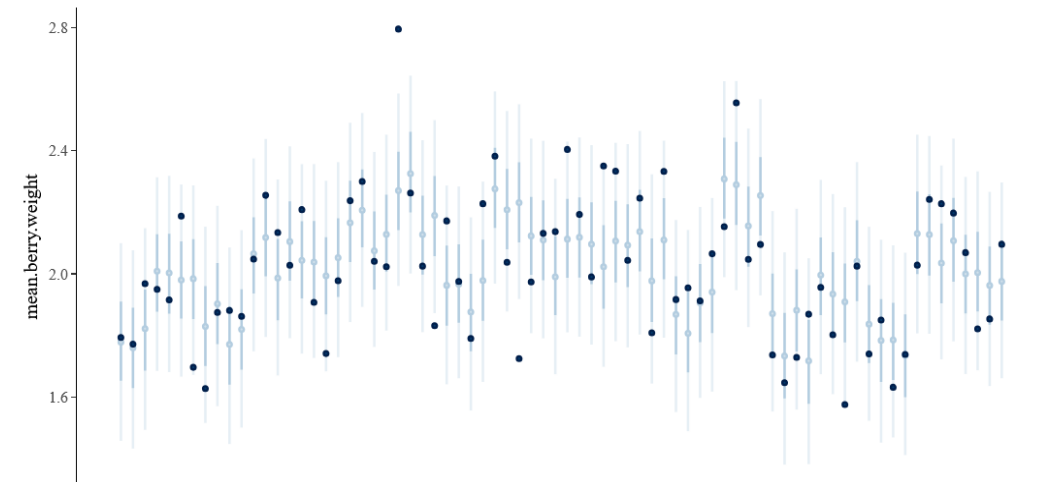
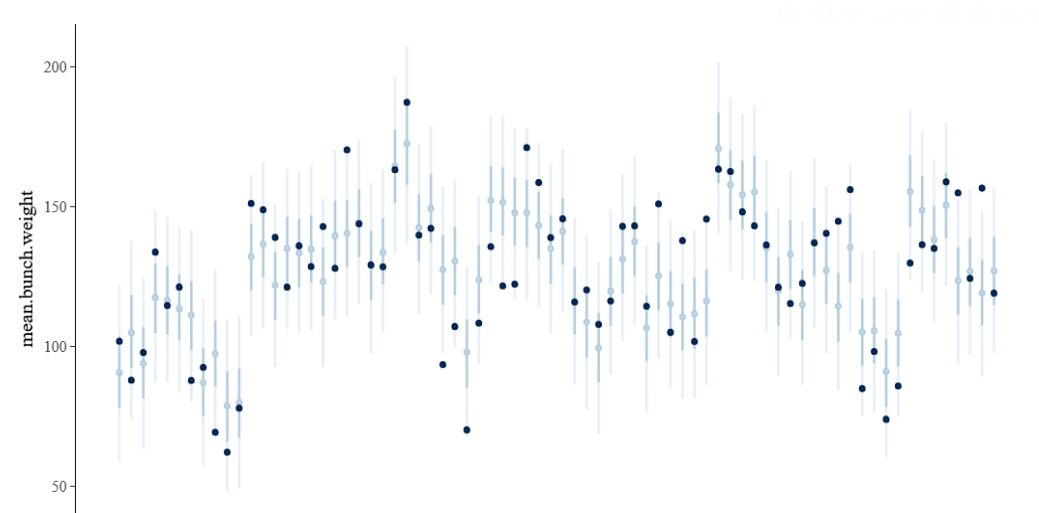
- **workflowsets**: Systematic generation of all preprocessing, models, and tuning combinations
- Efficient metric-based comparison and selection of workflows
- Stack workflowset to improve predictive performance (1 linear metamodel)
- **stacks**: tidymodels package for creating stacking ensembles

	XGBoost	Random forest	Neural network	Gradient boosting	GLM
<b>Mean imputation</b>	XB1	RF1	NN1	GB1	GLM1
<b>RW imputation</b>	XB2	RF2	NN2	GB2	GLM2
<b>KNN imputation</b>	XB3	RF3	NN3	GB3	GLM3
		X			
<b>Grid search</b>	<b>Random search</b>	<b>Bayesian optimisation</b>			
	= 45 workflows				



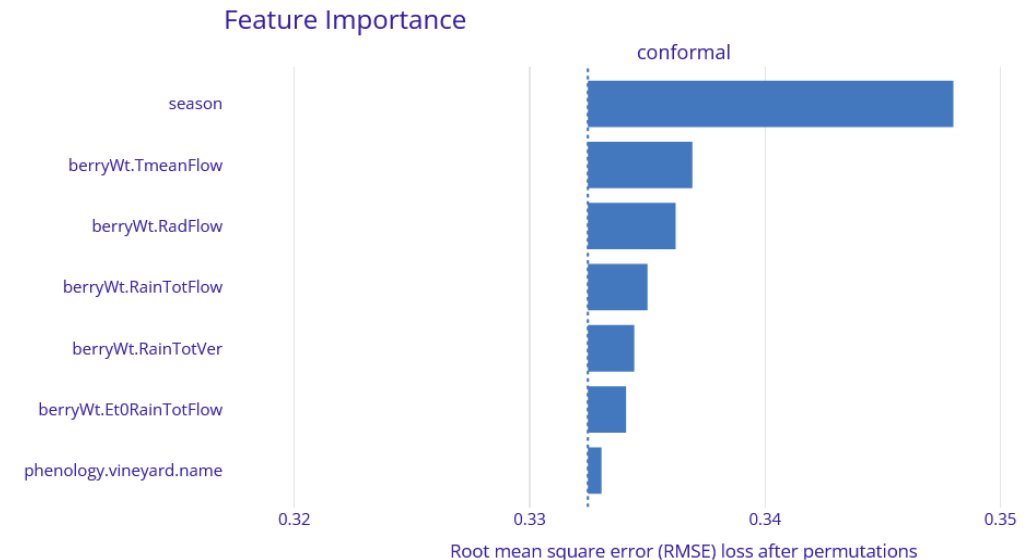
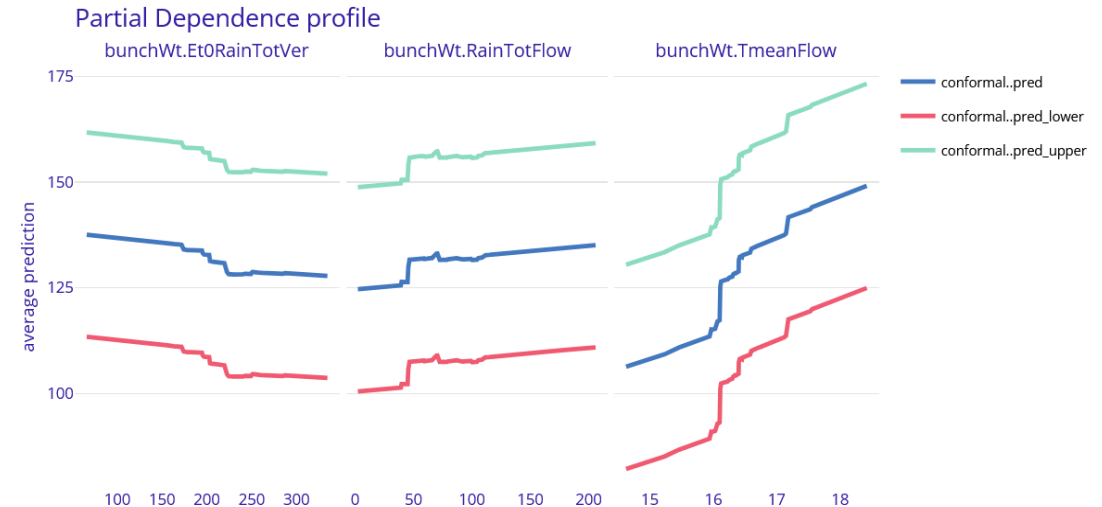
# Conformal inference

- Model agnostic: Produce prediction intervals for any ML model
- Quantifies predictive uncertainty: Risk-sensitive applications
- Theoretically guaranteed coverage: e.g. 95% intervals contains truth ~95% of the time
- No distributional assumptions. Exchangeability assumption
- **probably:** tidymodels package for conformalisation and recalibration



# Model interpretability

- Makes black-box model decisions interpretable to humans
- Detect bias, leakage, or unexpected behaviour
- Debugging and model improvement
- Increases trust with stakeholders and decision-makers
- **DALEX**: Model interpretability toolbox; offers tidymodels integration



# From ML model to API

- **vetiver**: Packages, version-controls, and deploys models
  - Consistent model-to-API process
  - Bridges gap between analysis and deployment
- **plumber**: Expose models as lightweight web apps (REST APIs)
  - Integration with apps, dashboards, and services



Return predictions from model using 12 features

**POST** /predict

REQUEST

REQUEST BODY application/json

**EXAMPLE** SCHEMA

```
[
  {
    "season": 0,
    "phenology.vineyard.name": 0,
    "berryWt.TmeanFlow": 12,
    "berryWt.RadFlow": 22,
    "berryWt.RainTotFlow": 51,
    "berryWt.RainTotVer": 26,
    "berryNum.RainTotVer": 26,
    "bunchWt.TmeanFlow": 12,
    "bunchWt.RadFlow": 22,
    "bunchWt.RainTotFlow": 51,
    "bunchWt.RainTotVer": 26,
  }
]
```

API Server <http://localhost:8787/p/2d859d21/>  
Authentication Not Required

FILL EXAMPLE CLEAR TRY

Response Status: OK:200  
Took 106 milliseconds

CLEAR RESPONSE

**RESPONSE** RESPONSE HEADERS CURL

```
{
  ".pred": [
    {
      ".pred": 30.0572,
      ".pred_lower": 26.8809,
      ".pred_upper": 33.2334
    }
  ]
}
```

Copy

RESPONSE

200 500 default

OK

**EXAMPLE** SCHEMA

application/json

# Dashboarding and model cards



- Shiny dashboards turn model outputs into interactive tools for decision-making
- vetiver model cards document model purpose, performance, and limitations

**GRAPEVINE YIELD PREDICTION**

Results | Scatter | Predictions | Histograms | Data Table | Summary | **Model Card** | Plot

### MODEL CARD: TIDYMODELS MACHINE LEARNING MODEL FOR GRAPEVINE YIELD PREDICTION (MARLBOROUGH, NEW ZEALAND)

2026-05-02

A [model card](#) provides brief, transparent, responsible reporting for a trained machine learning model.

#### MODEL DETAILS

- Developed by James Bristow
- Name: grapevine\_yield\_ensemble
- Version: 20251003
- Framework: tidymodels
- Target: grapevine yield (kg/vine)
- Training data: vineyard block-level agronomic + climate data
- If you have questions about this model, please contact [James Bristow](#)

#### INTENDED USE

- Predict grapevine yield in Marlborough vineyard blocks using seasonal climate data.
- Intended users: viticulturists, vineyard managers, agricultural researchers.
- Not intended for financial forecasting or automated operational decision-making without expert review.
- Not valid for use outside Marlborough without retraining.

#### IMPORTANT ASPECTS/FACTORS

- Key drivers: Seasonal rainfall and irrigation. Canopy and pruning strategy.
- Strong vintage effects (year-to-year climate variability).
- Spatial variability across vineyard blocks is significant.

#### METRICS

- The metrics used to evaluate this model are root mean squared error and mean absolute error.
- These metrics are computed via the [yardstick package](#).
- We chose these metrics because they are popular and interpretable evaluation metrics for predictive accuracy.

#### TRAINING DATA & EVALUATION DATA

- The training dataset for this model was grapevine data collected from four vineyards within Marlborough, New Zealand.
- The evaluation dataset used in this model card is an 80-20 train-test data split.

#### ETHICAL CONSIDERATIONS

↓ DOWNLOAD DATA

↓ DOWNLOAD CARD

↓ DOWNLOAD PLOT

# Containerisation and infrastructure



- S3: Storage
  - *Store it anywhere*
  - Store data, models, and artifacts centrally for reuse via pins
- Docker: Reproducibility
  - *Run it anywhere*
  - Package models and R environments for consistent execution
- Kubernetes: Scalability
  - *Run it everywhere*
  - Orchestrate deployments so models can scale and serve anywhere



Amazon S3



docker



kubernetes

# Conclusion



- From ad-hoc scripts and notebooks to reproducible pipelines
- Adoption of DevOps principles within ML workflows
- Treat models as storable artifacts
- For more: <https://github.com/Plant-Food-Research-Open/r-pipeline-development-workshop/tree/main>

*Good models matter.*

*But good pipelines decide whether they ever get used.*

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# Presentation disclaimer



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