Machine learning based ranking for risk

Intelligent risk recommendations for ACS

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Agenda

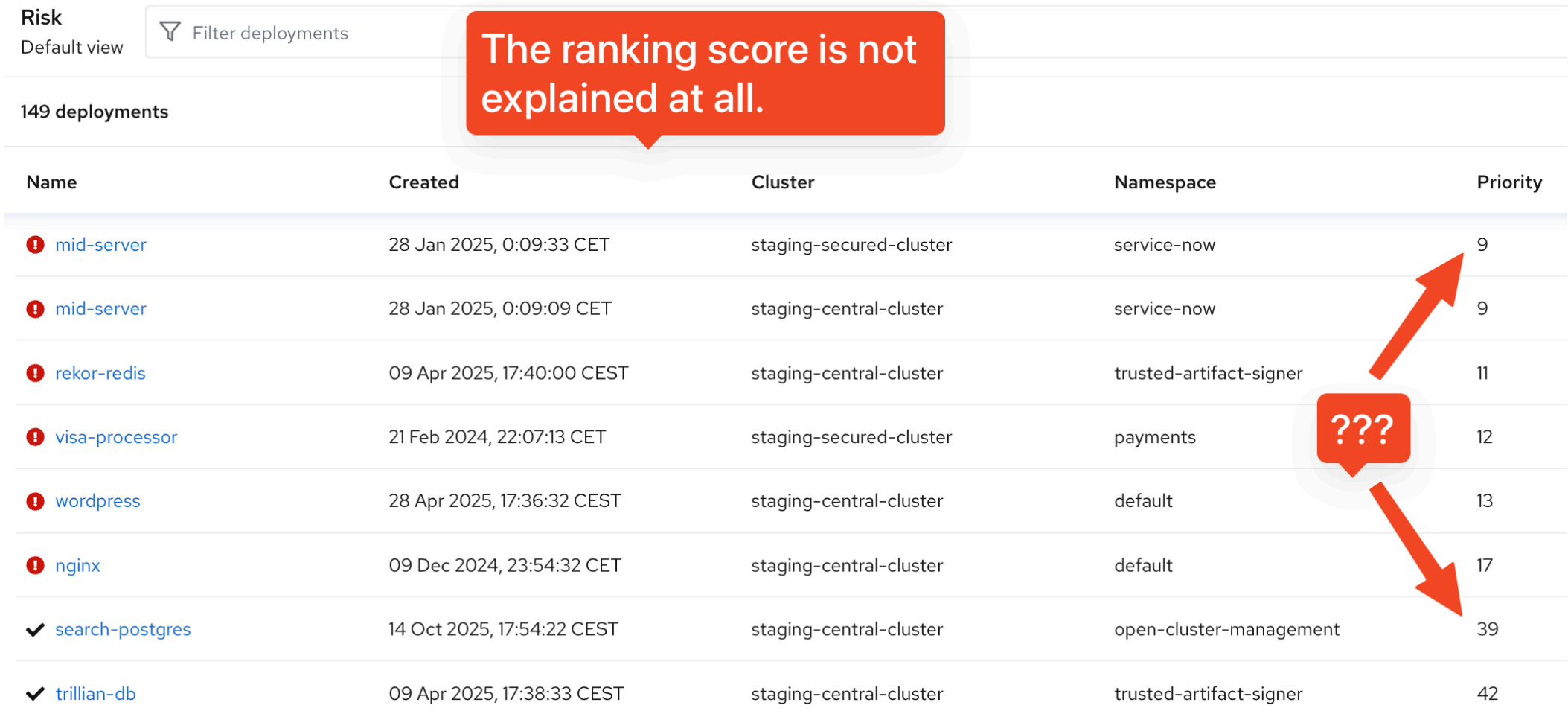
1. **The Challenge**: Why we need machine learning for risk ranking
2. **The Algorithm**: How a random forest works
3. **The Training**: From Central data to trained model
4. **The Predictions**: How to rank deployments in production
5. **Vibe Coding**: Current prototype status

THE CHALLENGE

What Is Risk?

- **ACS monitors thousands of deployments** across customer clusters
- Each deployment has **dozens of security characteristics**:
  - Policy violations
  - CVE vulnerabilities
  - Privileged containers
  - Network exposure
  - Process anomalies
  - … and many more
- **Question:** Which deployments should security teams focus on first?

The Existing Risk Feature



Current risk assessment in ACS

Shortcomings of Current Approach

- 🔒 **Intransparent**
  - The risk score is baked into ACS with a complex formula.
  - Customers cannot understand or validate how scores are calculated.
- ⚙️ **Inflexible**
  - Does not adapt to customer needs or emerging trends.
  - One-size-fits-all approach across all environments.

Current Approach: Rule-Based Multipliers

Feature multiplication:

```
Risk Score =
  Policy Violations ×
  Process Baseline ×
  Vulnerabilities ×
  Risky Components ×
  Component Count ×
  Image Age ×
  ...
```

Drawbacks:

- **Hardcoded formulas**
  - Manually tuned thresholds and weights
- **Cannot reverse the calculation**
  - Multiplied scores lose individual feature information

Example: Image Age Calculation

```
// Creates a score that is:
// A) No risk when daysSinceCreated is < penalizeDaysFloor
if imageAgeInDays < penalizeDaysFloor {
    return
}

// B) Increases linearly between penalizeDaysFloor and penalizeDaysCeil
daysSincePenalized := imageAgeInDays - penalizeDaysFloor
scaledDays := float32(daysSincePenalized) / float32(penalizeDaysCeil-penali
riskScore = float32(1) + float32(scaledDays*(maxMultiplier-1))

// C) Is 1.5 when duration is > penalizeDaysCeil
if riskScore > maxMultiplier {
    riskScore = maxMultiplier
}
```

The Machine Learning Solution

- **Learn** from real or synthetic training data.
- **Identify** which security features matter most.
- **Rank** deployments by learned feature weights.
- **Explain** what features contribute to high risk scores.
- **Improve** continuously as new data arrives.

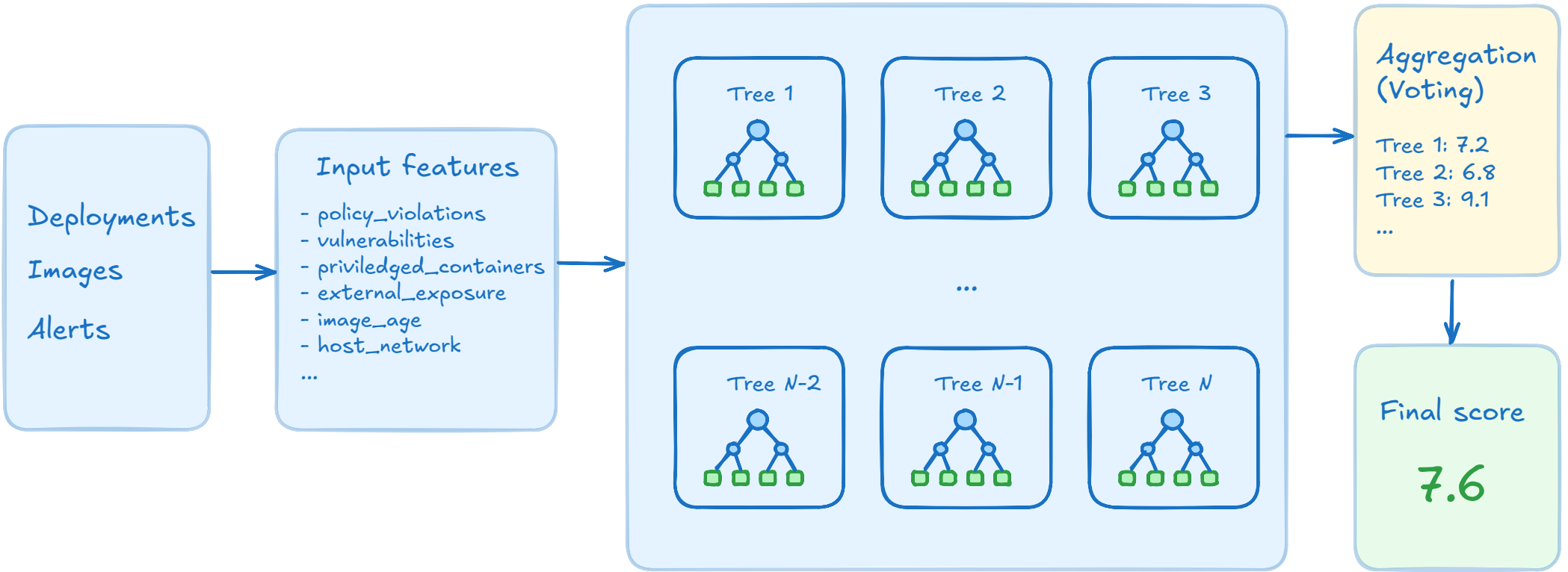
THE ALGORITHM

Random Forest: The Committee Approach

Analogy: Assessing fire risks for a house.

- Instead of **1 inspector** with a rigid checklist…
  - … ask **1000 inspectors**.
- Each inspector looks at different factors:
  - Electrical wiring + smoke detectors
  - Flammable materials + escape routes
  - Building age + maintenance history
- **Final assessment** = average of all 1000 opinions

Random Forest Architecture



Example: One Decision Tree

```
Is vulnerability_score > 7.5?
├─ YES → Is privileged_container_ratio > 0.5?
│         ├─ YES → Risk Score = 8.2
│         └─ NO → Is external_exposure = 1?
│                  ├─ YES → Risk Score = 6.5
│                  └─ NO → Risk Score = 4.1
└─ NO → Is policy_violation_score > 3.0?
         ├─ YES → Risk Score = 5.0
         └─ NO → Risk Score = 2.3
```

Final Prediction: Average of 1000s such trees

Why Random Forest?

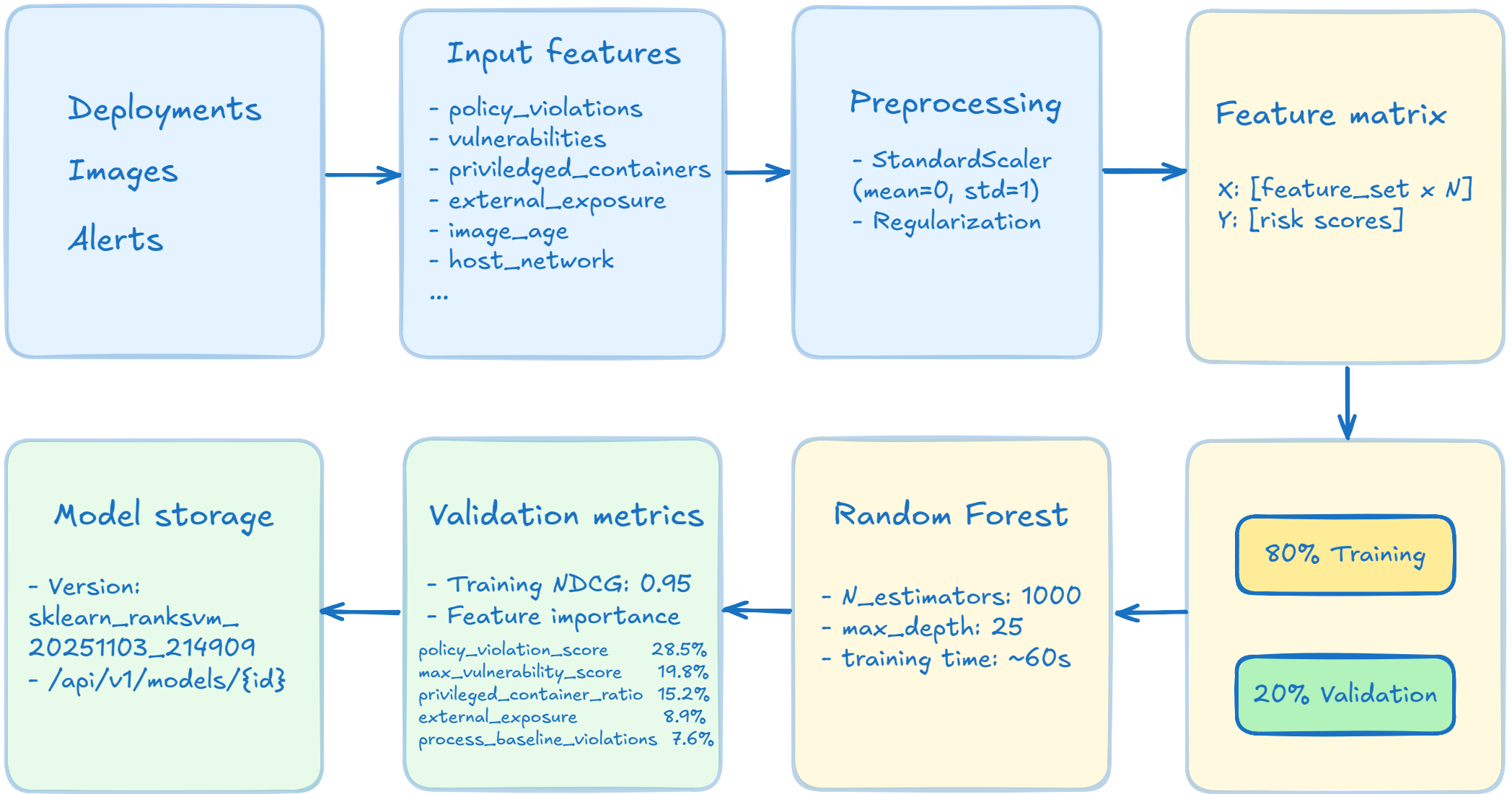
1. ✅ **Robust against outliers**
   - If one tree makes a mistake, 999 others can correct it.
2. ✅ **Handles complexity**
   - Learns non-linear relationships automatically.
3. ✅ **Provides Explanations**
   - Feature importance: which security issues matter most.
4. ✅ **Simple Training**
   - No epochs, no backpropagation, no GPUs required.

Why not Random Forest?

1. ❌ **Just a regression algorithm**
   - No actual AI. Not in the training data -> won't be learned.
2. ❌ **Supervised learning**
   - Predictions are only as good the training input. Feature engineering matters.
3. ❌ **Retraining**
   - Learning new things requires new training data + model retraining.

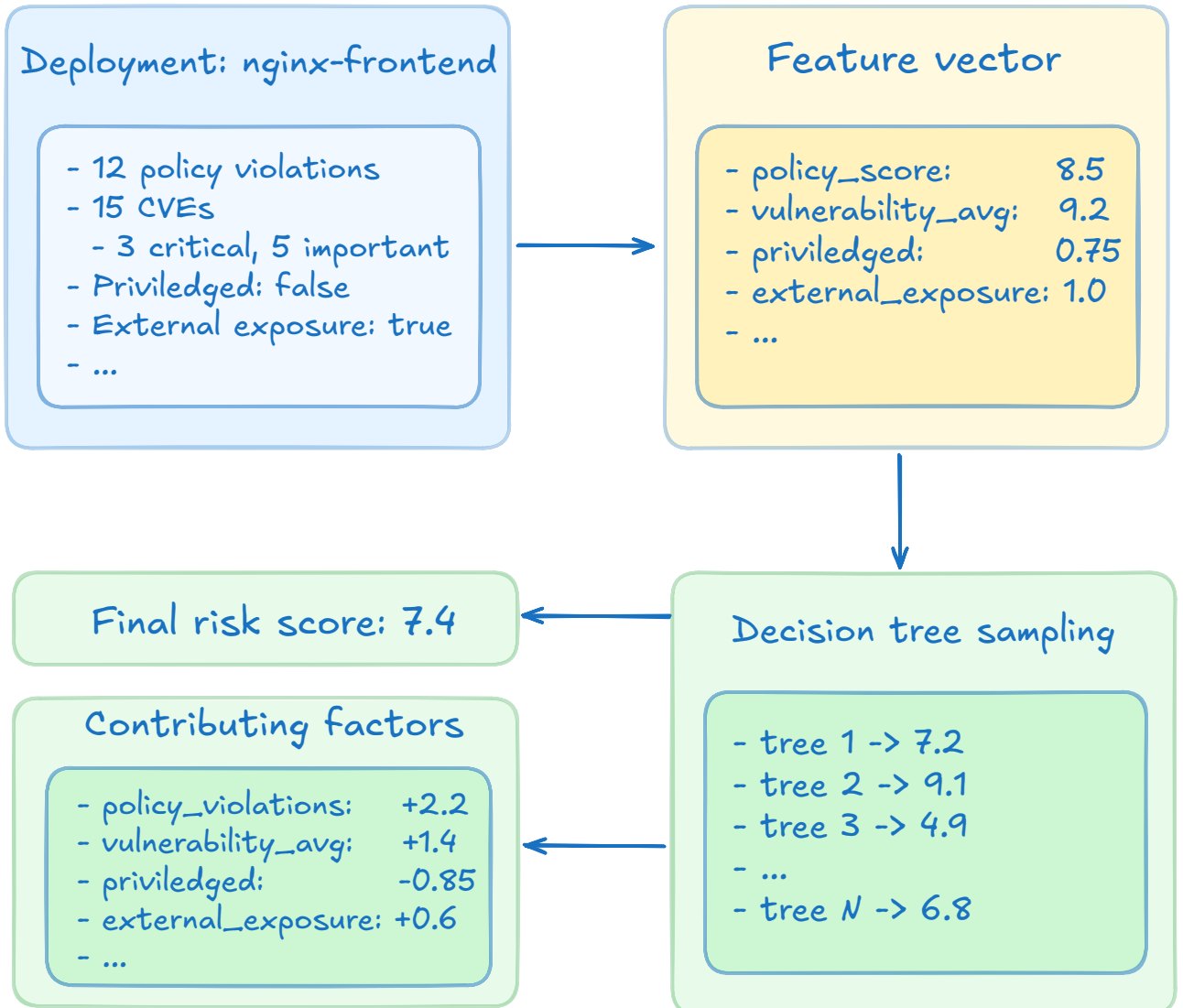
THE TRAINING

End-to-End Training Flow



THE PREDICTIONS

Prediction Flow



Feature Importance: What Matters?

Example: Top 5 most important features

```
1. policy_violation_score      28.5%
2. max_vulnerability_score     19.8%
3. privileged_container_ratio  15.2%
4. external_exposure            8.9%
5. process_baseline_violations  7.6%
```

- **Insight:** Policy violations and critical CVEs drive risk ranking more than other factors.
- **Detail:** Calculated for training data and each prediction.

Performance Metric: NDCG

NDCG = Normalized Discounted Cumulative Gain

- Measures **ranking quality** on 0-1 scale
- **1.0**: perfect ranking, **0.0**: worst ranking

Example:

```
True ranking:  [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
Model ranking: [1, 2, 3, 4, 5, 6, 7, 9, 8, 10]
                                    ↑ Small error at bottom
NDCG ≈ 0.98  (98% as good as perfect ranking)
```

Typical Performance

Training Metrics

- NDCG: **0.75-0.95**
- Training time: **~60 sec**

Model Characteristics

- Feature count: **~20**
- Training samples: **100-1000**
- Model size: **~20 MB**
- Trees: **1000**

Validation **NDCG > 0.75** means model ranks deployments reasonably well!

VIBE CODING

Current Prototype

🤖 Model

- Training pipeline with Central integration
- Feature extraction for deployments + images
- RandomForest model with versioning
- Validation with NDCG tracking

📦 Deployment

- Python container with FastAPI REST service
- Model persistence to local/remote storage

Questions?

Future Improvements

- Fine-tune different models and improve feature extraction.
- Use LLMs to generate advanced training data.
- Implement back propagation of user driven risk decisions.
- Integrate prototype with ACS UI.

Resources

- Code: `stackrox/ml-risk-service`
- Docs: `learning.md`