FLOW STRESS PREDICTION

ALUMATECH PLATE STRETCHING

Kevin Yeoman

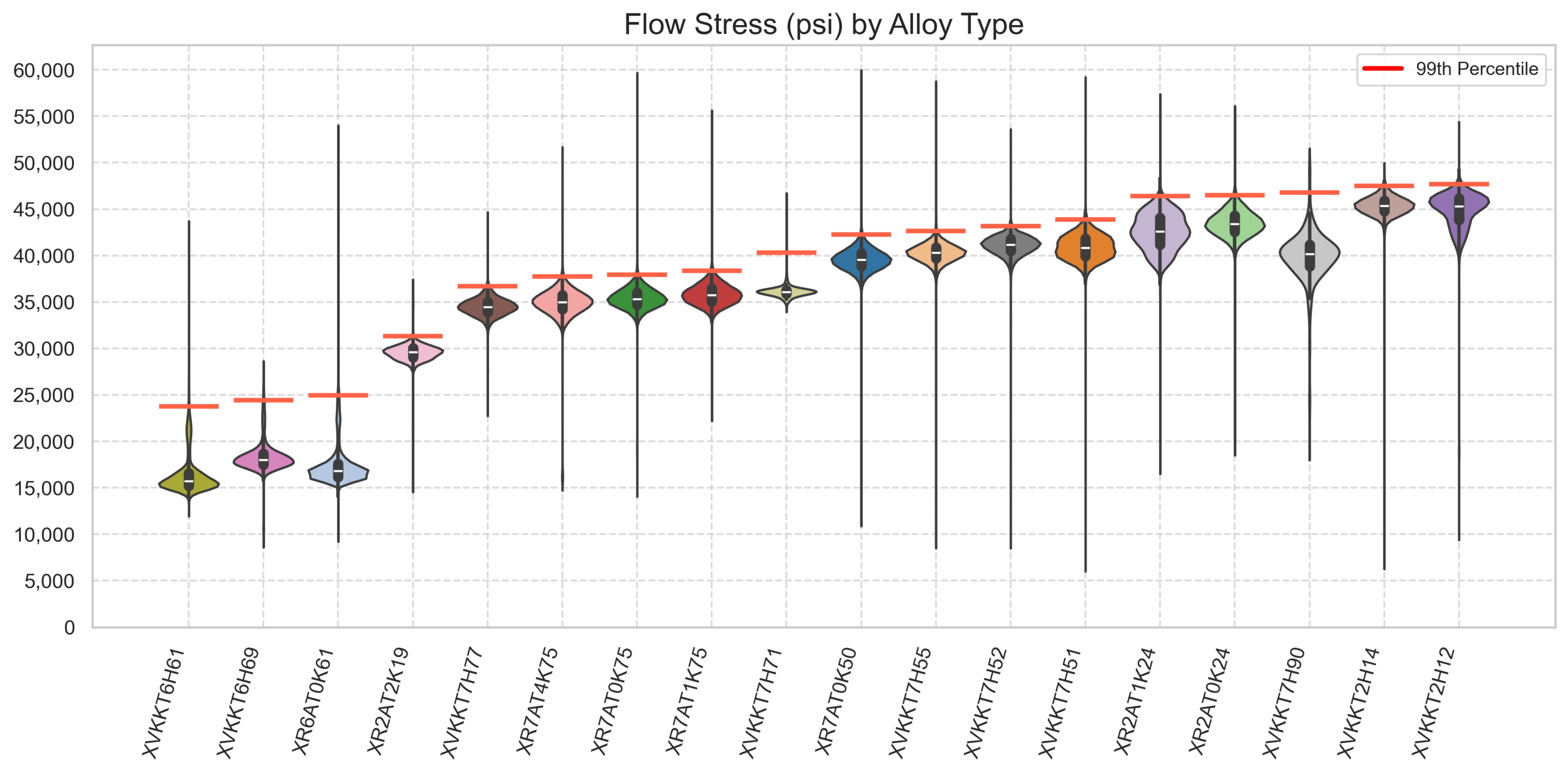
Introduction

- Previous method: Simple averages → risk of underestimating force
- New approach: Use 500k+ stretch records to build a predictive model
- Goal: Accurately estimate flow stress for any alloy/plate.

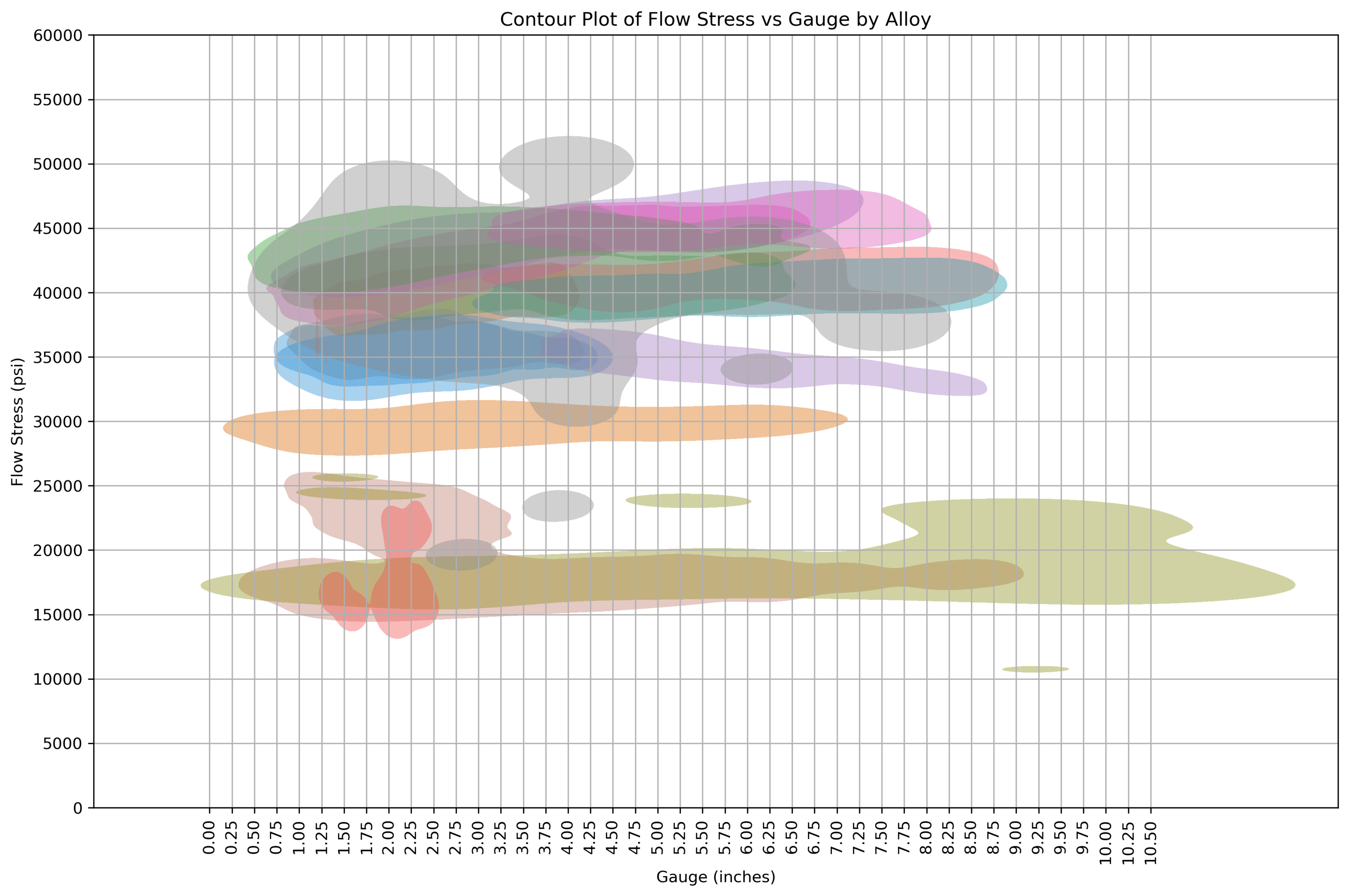
Data Prep

- Source: ~486k records (2013–2023) with key plate specs
- Cleaned: Removed errors, outliers, rare alloys
- Final Set: 18 alloys → high-quality data ready for modeling

Explore Alloy Distribution

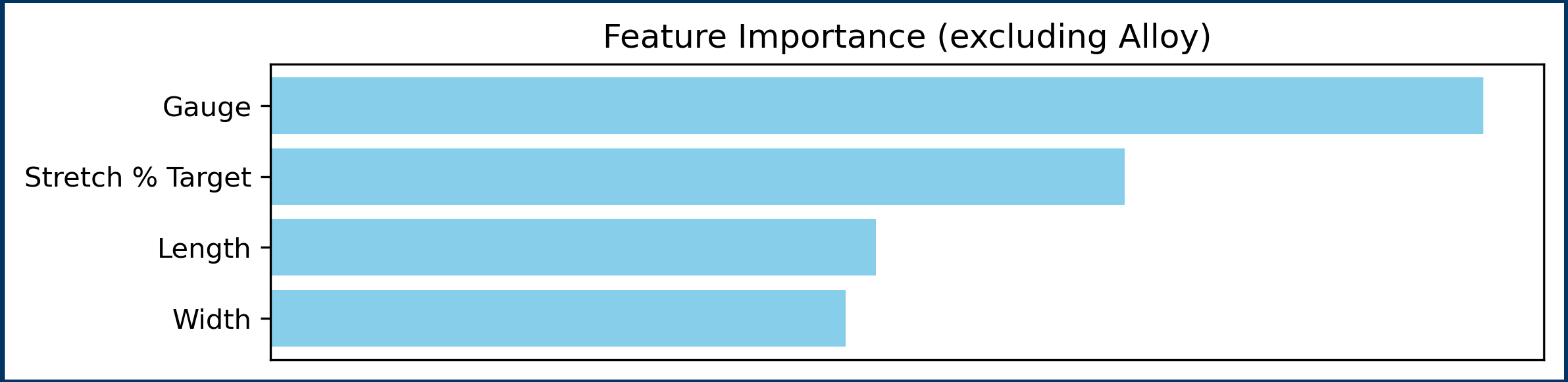


Explore Distribution Clustering



Key Insights

- Two Stress Clusters: ~15–20 ksi vs ~35–45 ksi → alloy-driven
- Main Drivers: Alloy & thickness
- Width, length, stretch % = minor impact



Modeling Approach

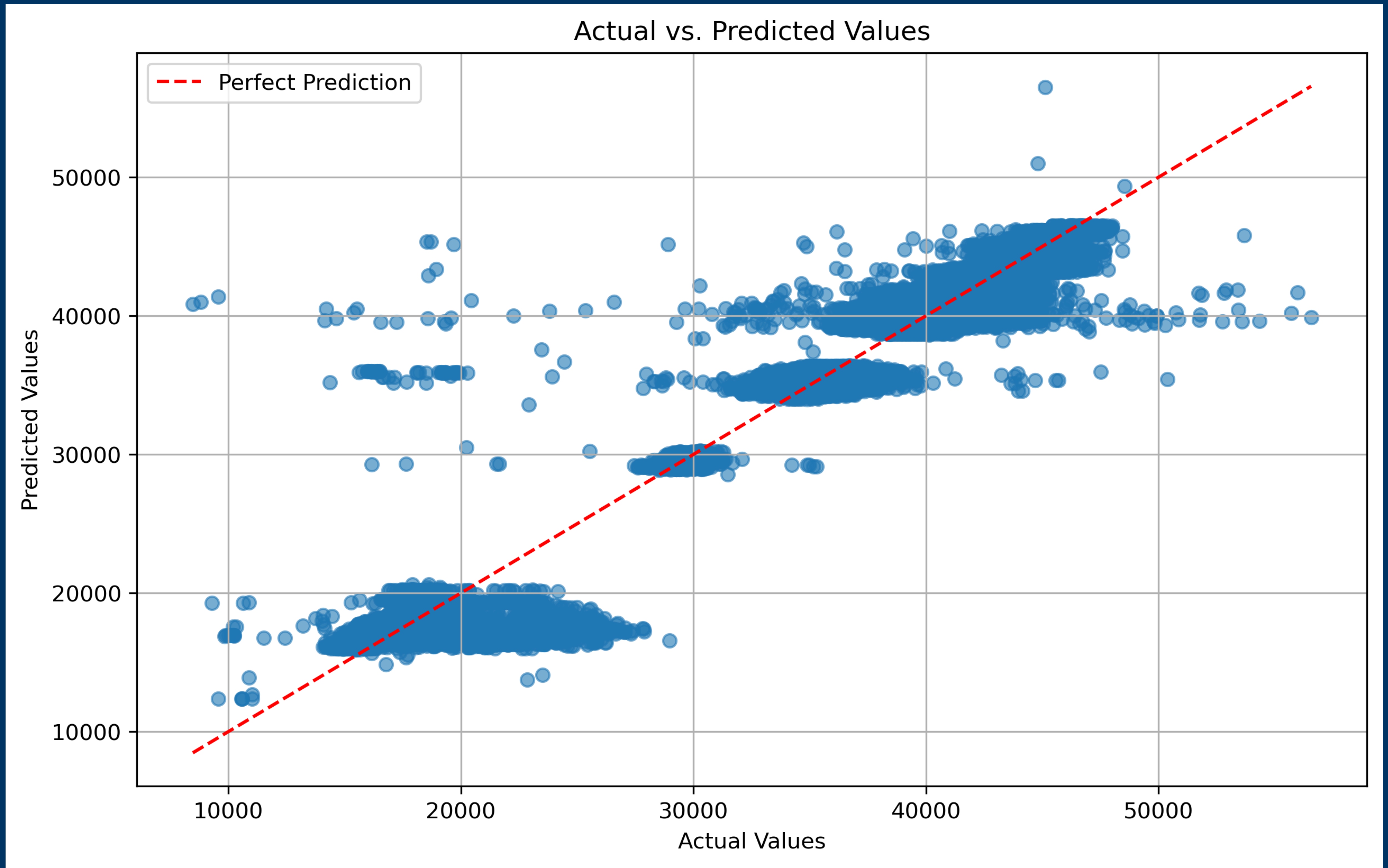
- Models: Linear Regression, Random Forest, LightGBM (99th percentile)

- Inputs: Alloy (one-hot), thickness, width, length, stretch %

- Training: 80/20 split, 5-fold CV. Regularization had minimal effect

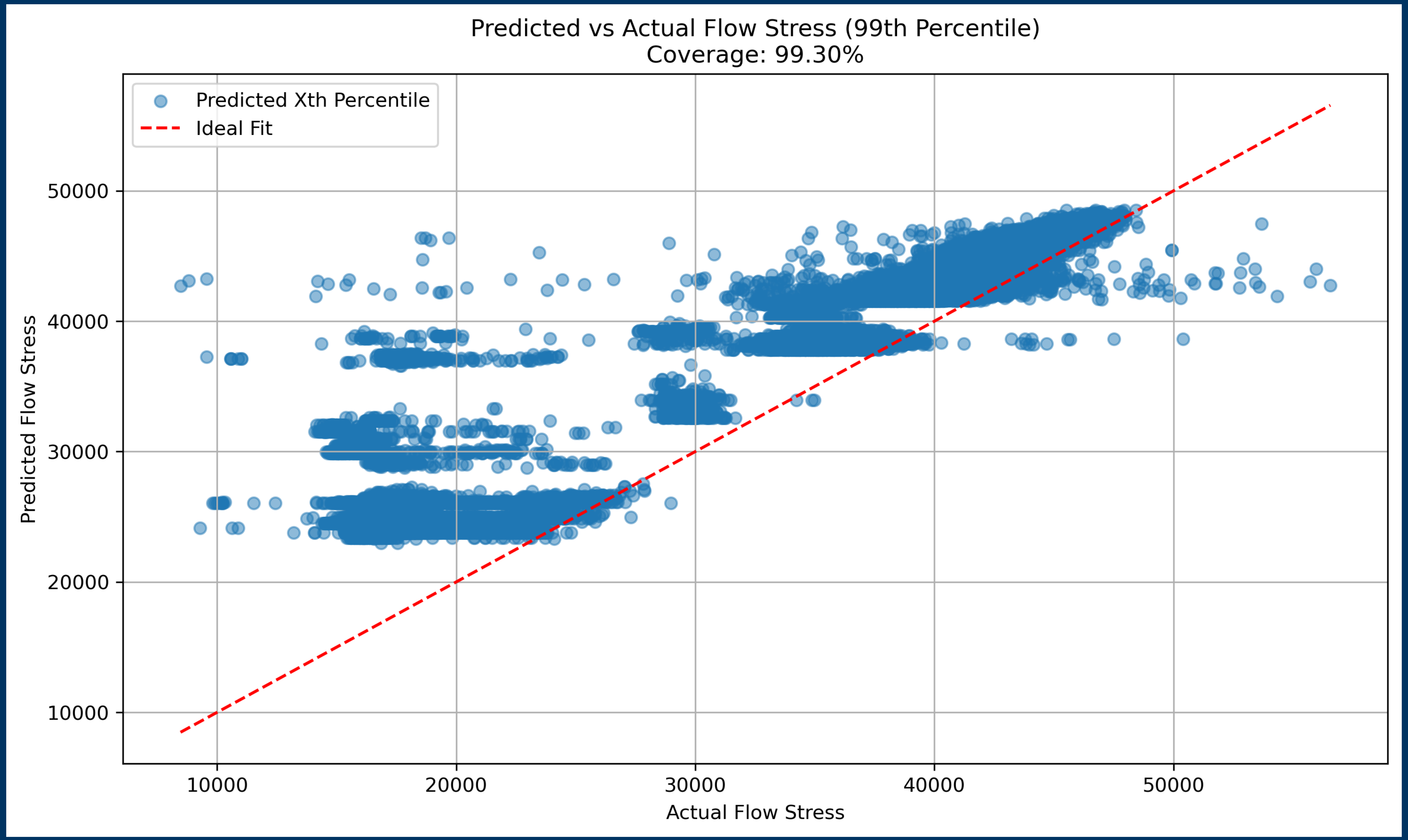
Model Accuracy

- Random Forest: $R^2 = 97.7\%$, RMSE = 1.4 ksi
- Linear Model: Nearly as good
- Top Predictors: Alloy & thickness (>95% of RF splits)
- Prediction Match: Close alignment with actual values

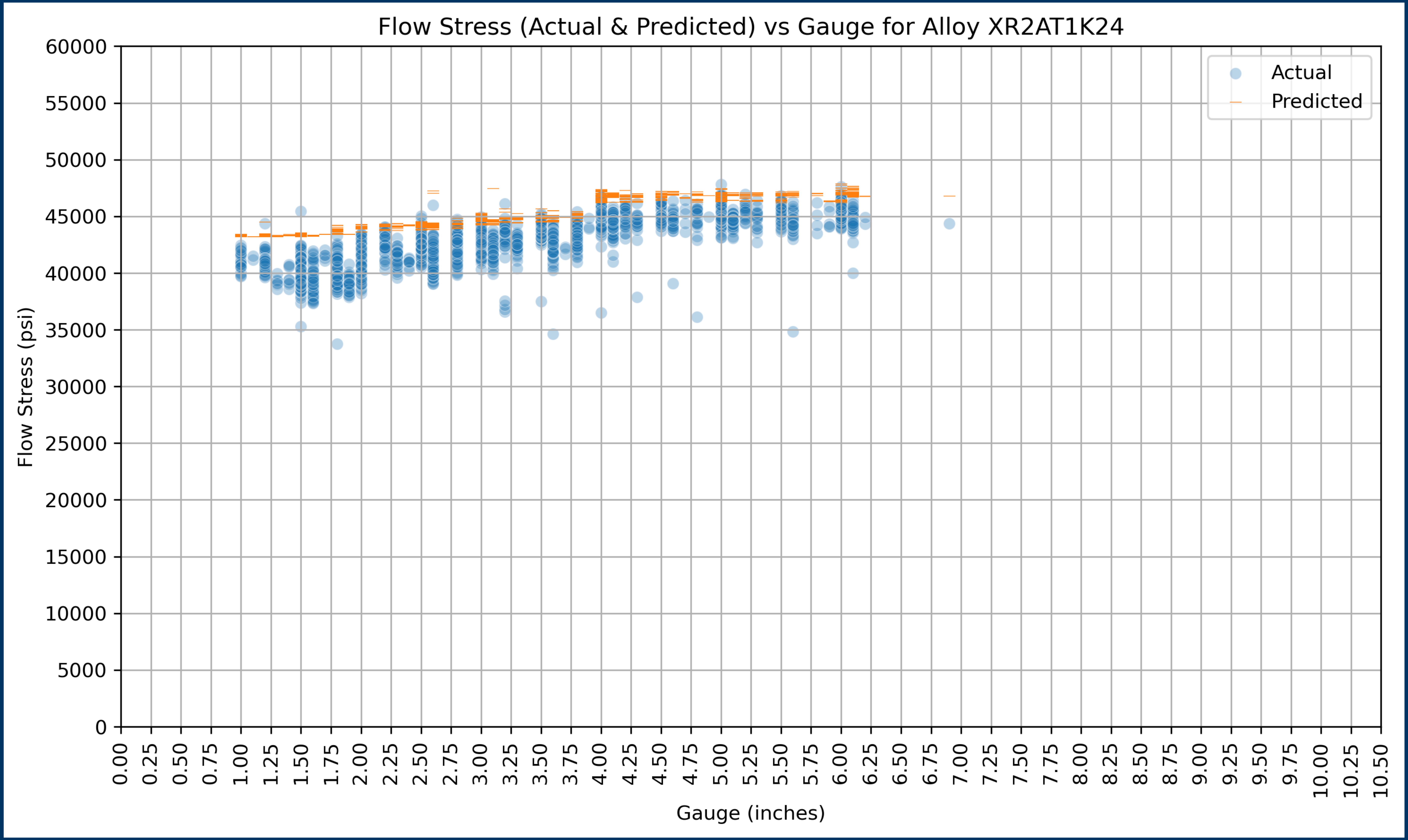


Modeling for Conservative Estimate

- LightGBM (99th percentile): Conservative estimates
- 98% of actual stresses below prediction
- Avg safety margin: ~3.8 ksi



Individualized LGB per Alloy



Recommendations

- Design Check: Use model before stretching
- Smart Scheduling: Plan high-force stretches carefully
- QC: Compare predicted vs actual; investigate big gaps

Next Steps

- Build alloy-specific models
- Retrain yearly with new data
- Deploy as app or Excel tool
- Explore digital twin integration

Conclusion

- Reliable & Safe: ~3% error, 99% assurance
- Operational Gains: Predict forces, avoid overloads
- Innovation: Faster product dev, better quality
- Action: Deploy model, follow recommendations