The Hidden Threats of Decay in Al

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Celeste Fralick, Ph.D. Chief Data Scientist, Senior Principal Engineer Office of the CTO McAfee, LLC

Celeste_fralick@mcafee.com



Model Reliability Begins During Development

Do you really have a clean data pipeline?

- How do you know? Where did the data come from?
- Is it balanced? Sparse? Dense? Why or why not?
- Have there been data manipulations that impact a sample: filters, caches, down-sampling, etc?
- Is the sample & pipeline repeatable and reproducible?

"Who, What, When, Why, Where and How"

Model Reliability Begins During Development



Check for overfitting *please*

- <u>Training dataset</u>: data used to fit the model
- <u>Validation dataset</u>: data used to validate the generalization ability of the model or for early stopping, *during the training process*.
- <u>Testing dataset</u>: data used to for other purposes other than training and validating.

https://stats.stackexchange.com/questions/401696/validationaccuracy-vs-testing-accuracy

Model Reliability Begins During Development

Optimize loss function & target model stability

- 3 Models & at least two error rates: ROC and non-ROC (RMSE) (Caruana 2004)
 - Confidence in predictions
- Comparing models:
- 1. Covariance Inflation Covariance (CIC): covariance input vs predictor response (*Tibshirani 1999*)
- 2. Perturbing training data to overcome local maxima *(Elidan 2002)*
- 3. Dual perturb and combine algorithm perturbs test examples w/ random noise (Geurts 2001)





- 2 Samples with w/ground truth y1=1, y2=0
- Green square: both classified correctly
- Yellow square: at least 1 classified incorrectly
- Red square: both classified incorrectly
- 3 Models u (least), v, (better) z (best)





Post-release Analytic Review

- What's changed? Why?
- What are the critical metrics/time?
- Check distributions, error rates
- Has the ground truth evolved?
- Have labels or data evolved?
- How do you monitor change?

Adversarial Machine Learning: Protect Against Model Hacking





99.68% penguin

93.07% frying pan





Perturbation



Adversarial Machine Learning: Model Hacking

- Attack > Detect > Protect
- White/gray/black box testing with prioritized vulnerable features
- Retraining increases
 test accuracy from 73% >92%
 by detecting evasion attack
 without changing original
 detection rate.
- What happens if FP/FN 1 ?



Explainability (XAI) Techniques Can Help Understand Decay



- Use ML to assess magnitude & direction
- XAI algorithms: LIME, Grad-CAM, SHAP, etc.
- Applicable to intrusion detection, malware
- Understanding unknowns, assessing changes in model field reliability

Polymorphisms and Decay Threaten Model Integrity

94%

executables

are

polymorphic

- Concept drift (changing labels/time)
 - Loss of predictability
 - "No change in distribution"
 - Telemetry / internal
- Data decay (new data variety/time)
 - New data, new architecture
 - New categories> labels aren't changing
- Learning rate appropriate?

Minimizing Threats to Decay

- 1. Monitor and feedback > model reliability
- 2. Pipeline integrity: "5 W's & 1 H"
- 3. Incorporate risk management in data science life cycle & AFTER
- 4. Adversarial Machine Learning (AML/model hacking):
 - Analytic defense: Adversarial Retraining using Examples, Distillation, Feature Squeezing, Noise Addition, RONI, FGSM
 - XAI and vulnerability propensity
- 5. Explainability (XAI)
 - Apply XAI techniques post-dev: LIME, Grad-CAM, SHAP

Combination will minimize threats!



Thank you.



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