Assured Machine Learning

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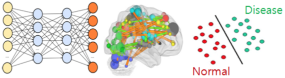
June, 2018

Machine Learning Applications in Safety-Critical Environments

- Decision making in life-threatening conditions (Machine-Learning (ML) based medical decision support systems)

Figure: ML Based Brain Disease Diagnosis[1]



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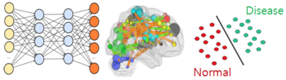
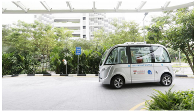


Figure: Surgical Robots[2]

Machine Learning Applications in Safety-Critical Environments

- Decision making in life-threatening conditions (Machine-Learning (ML) based medical decision support systems)
- Robots (surgical robots, industrial robots, etc.)
- Autonomous vehicles

Figure: Autonomous Shuttle



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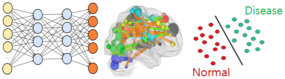

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Challenges to Safety Assurance

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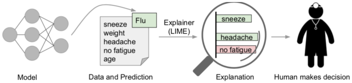
- Error Rate:The estimate of error rate of a ML model with respect to the test data is not reliable
- Instability: A small change in the training process may produce a different result, and hence it is difficult to debug models or reuse parts of previous safety assessments.
- Difficulty in verification: Formal verification of ML components is a difficult, and somewhat ill-posed, problem due to the complexity of the underlying ML algorithms and large feature spaces

Potential Strategies for Safety Assurance

- Interpretability & Transparency: Improve the interpretability & transparency of the ML component

Figure: Explanations improve trust in prediction [3]



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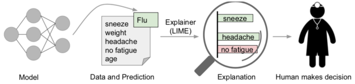

Technique used in ML when predictions cannot be given confidently is the reject option [4]

$$\hat{y}(x) = \begin{cases} -1 & \text{if } \phi(x) \leq t \\ \text{reject, if } \phi(x) \in (-t, t) \\ 1 & \text{if } \phi(x) \geq t \end{cases}$$

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- Interpretability & Transparency: Improve the interpretability & transparency of the ML component
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- Abstract: Abstract the ML component and input feature space, and identify scenarios that could cause violation of safety specifications

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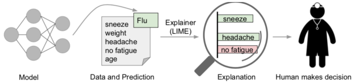

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- http://mlcenter.postech.ac.kr/healthcare
- https://www.wired.com/2015/03/google-robot-surgery/
- Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "Why should i trust you?: Explaining the predictions of any classifier." Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, 2016.
- Bartlett P L, Wegkamp M H. Classification with a reject option using a hinge loss[J]. Journal of Machine Learning Research, 2008, 9(Aug): 1823-1840.