A Grading Rubric for Al Applications



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- Head of AI for STEM at **Turnitin**
 - 35M students served at 150+ countries.
- Co-founder of **Gradescope**
- Co-organizer of Full Stack Deep Learning program
- PhD Computer Science at UC Berkeley





About Me





- Criteria for evaluating AI projects and applications
 - ...for funding (by governments, investors)
 - ...for deployment (by school systems, companies)
 - ...for development (by startups)



My Goal

Al Products: It's Early Days!

2018 survey of 300+ ML-involved developers from many industries

What phase are your Al projects in today?



https://www.nextplatform.com/2018/04/24/lagging-in-ai-dont-worry-its-still-early/



A Grading Rubric for AI Applications

Category

1. Task Formulation

2. User Interface / Performance Requirements

3. Technical Difficulty

4. Initial Data Moat

5. Data Flywheel





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5. Data Flywheel





Task Formulation

• Is the problem well defined, with clear metrics?



Х



Task Formulation

- No, Al is a magical solution to an unsolved, unmeasurable problem.
- **Example**: Al for achieving happiness



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Task Formulation • The task is complicated, but possible to measure performance.

- **Example**: giving students feedback on writing



Important to have experts involved in designing the product!



Helpful? OYes ONo I took care of this.

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Look for places to add transitions to improve the flow between your sentences. Transitions help to link ideas, compare and contrast ideas, sugges cause and effect, and can help the overall flow of your essay.





- The task is well-defined and there is a good baseline solution.
- **Example**: Facebook face recognition







Gary Chavez added a photo you might ... be in.

about a minute ago · 🔐

https://techcrunch.com/2017/12/19/facebook-facial-recognition-photos/



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- Is the Al autonomous or assisting the user?
- What % of time does AI need to make a prediction?
- How bad is it to make a mistake?





ML project **costs scale super-linearly** with performance requirements

. . .

99% Required accuracy

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99.9%

- fatal.
- **Example**: self-driving cars





AI must be 100% autonomous, predicting all the time, and mistakes are



- Al always has to predict, and user resents correcting mistakes.
- **Example**: speech-to-text transcription





- mistakes.
- **Example**: Gradescope Al-assisted answer grouping



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• Al doesn't have to predict every time, and user feels fine about correcting







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 $\frac{1}{2}x^2 + C$





User Interface and Performance Requirements for Education Applications

Aiding instructor

Lower

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Aiding student

Replacing instructor

Higher

Performance Requirements

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Technical Difficulty

- What are the technical resources needed to solve the problem?
 - (From analogs, academic literature, and expert opinions).



- The problem is several steps removed from today's technology.
- Requires world-class research team and unknown number of years.
- **Example**: intelligent tutor in all subjects and grade levels





- Reason to believe problem is solvable, but no working analog.
- Requires a research team and possibility of failure.
- **Example**: robot that teaches infants a second language.





Technical Difficulty



- Clear analogs, but technology is not yet mainstream.
- Requires capable engineers and a fixed time frame.
- Example: recognize handwritten math





Technical Difficulty

https://twitter.com/lvlzay_sci/status/1085501430767804416

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Initial Data Moat

- Defensible AI means proprietary data
 - (This is why Google/Facebook open-source their AI code)
- Is raw data available?
- How expensive it is to label?
- Can someone else get it?



Initial Data Moat

• Data is expensive to obtain and/or label, but there is no exclusivity.

• Example: satellite data





https://cdn-sv1.deepsense.ai/wp-content/uploads/2017/04/sample_image_from_the_training_set.jpg A Grading Rubric for Al Applications - Sergey Karayev



Initial Data Moat • Data is expensive to obtain and/or label, but there is exclusivity.

- **Example**: radiology data obtained through exclusive partnership







Initial Data Moat

- Data is exclusive and already labeled.



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• Example: detailed educational records of every student in Singapore

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- Are AI predictions monitored?
- Are wrong predictions corrected and system re-trained?
- Can users do this?



Data Flywheel

- Predictions are not monitored or corrected
- **Example**: most AI products







Data Flywheel



https://rvpartners.com.au/avoid-flying-blind-what-you-can-measure-you-can-manage/





- Predictions are monitored, and users are able to improve them
- **Example**: Google Photos





Data Flywheel





Thu, Mar 28 \sim

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The ML model



https://becominghuman.ai - Venkatesh Tata

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The ML model





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https://developers.google.com/machine-learning/crash-course/production-ml-systems Turnitin - ML Learning Bytes - April 2019