

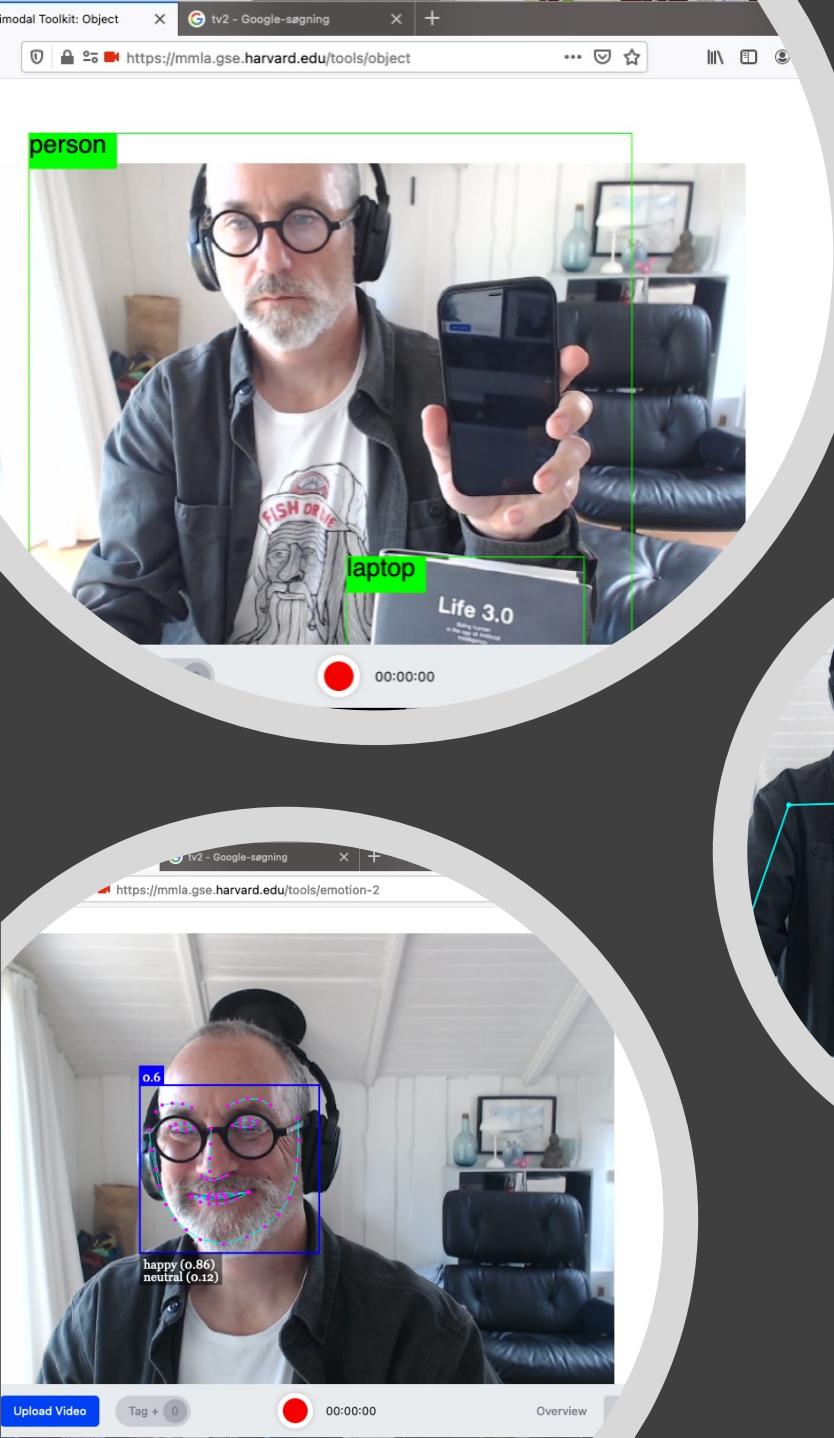


MMLA June 7

LA Course

Resources

- <https://mmla.gse.harvard.edu/tools>
- Paper: Hassan, J., Leong, J., & Schneider, B. (2021, April). Multimodal Data Collection Made Easy: The EZ-MMLA Toolkit: A data collection website that provides educators and researchers with easy access to multimodal data streams. In *LAK21: 11th International Learning Analytics and Knowledge Conference* (pp. 579-585).
- <https://doi.org/10.1145/3448139.3448201>



MMLA TOOLKIT

- EASIER WAY TO COLLECT SOME DATA

Google CoLabs

- <https://www.youtube.com/watch?v=inN8seMm7UI>
- https://colab.research.google.com/notebooks/intro.ipynb?utm_source=scs-index

05.08-Random-Forests.ipynb

File Edit View Insert Runtime Tools Help

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+ Code + Text Copy to Drive

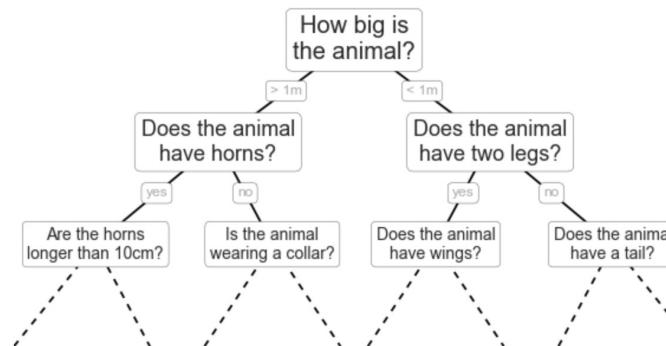
the sum can be greater than the parts: that is, a majority vote among a number of estimators can end up being better than any of the individual estimators doing the voting! We will see examples of this in the following sections. We begin with the standard imports:

```
[ ] %matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
```

▼ Motivating Random Forests: Decision Trees

Random forests are an example of an *ensemble learner* built on decision trees. For this reason we'll start by discussing decision trees themselves.

Decision trees are extremely intuitive ways to classify or label objects: you simply ask a series of questions designed to zero-in on the classification. For example, if you wanted to build a decision tree to classify an animal you come across while on a hike, you might construct the one shown here:

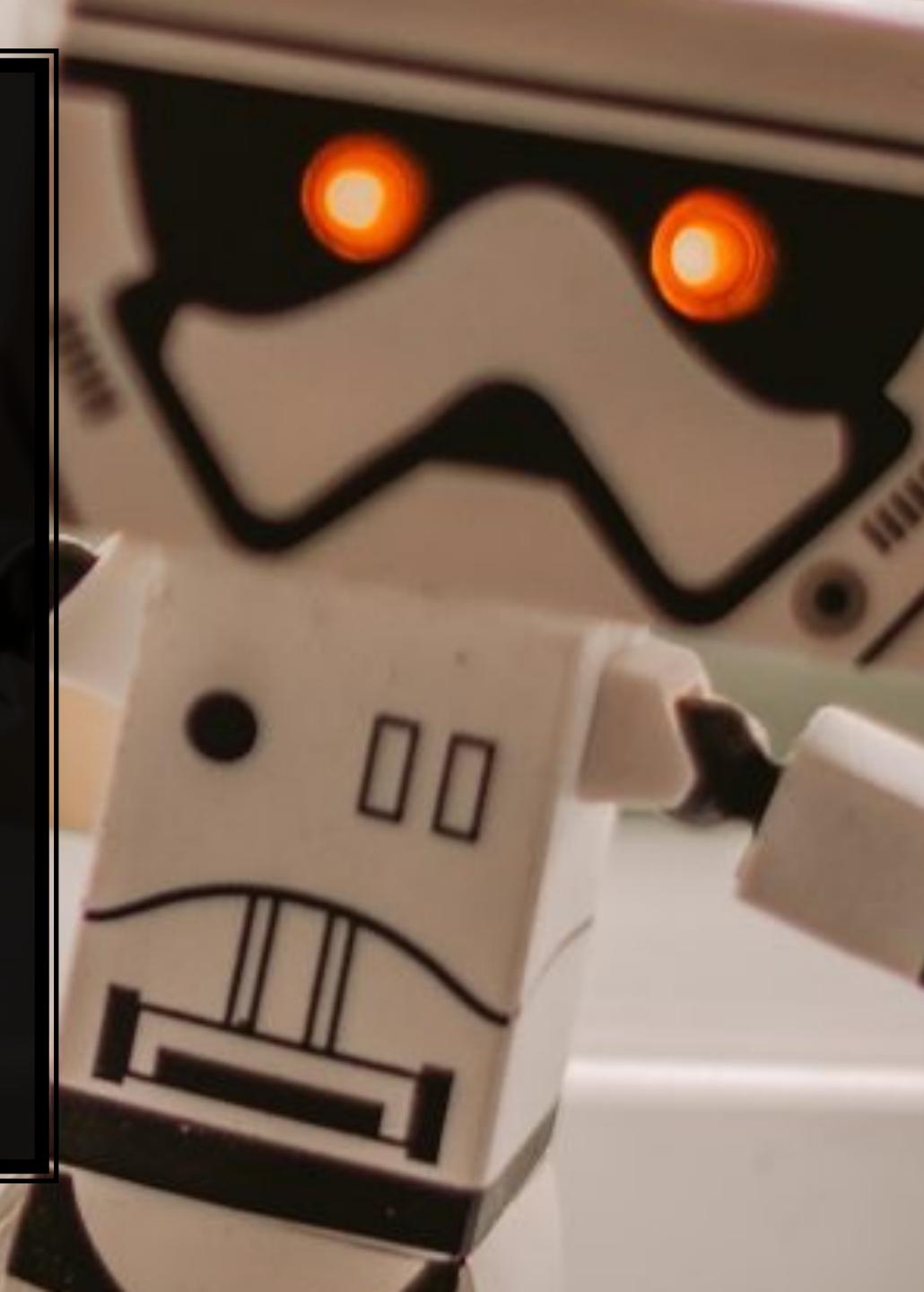


```
graph TD
    A[How big is the animal?] --> B[Does the animal have horns?]
    B -- yes --> C[Are the horns longer than 10cm?]
    B -- no --> D[Is the animal wearing a collar?]
    C -- yes --> E[ ]
    C -- no --> F[ ]
    D -- yes --> G[ ]
    D -- no --> H[ ]
    E --> I[Does the animal have wings?]
    F --> J[Does the animal have a tail?]
    G -- yes --> K[ ]
    G -- no --> L[ ]
```

figure source in Appendix

June 7 Pre-Seminar Work

1. Self-organize! Break into roughly 6 teams (4-5 people in a group) and plan to meet up virtually.
2. Do the Preliminary work in week 22 (May 31 - June 5) or earlier
3. Before your group meetings choose at least 1 or more articles (that you are interested in, individually to read, more is better) from the Literature.
4. For your group session conduct an open workshop using Speculative Design Fiction -
<https://www.invisionapp.com/inside-design/speculative-design/>
<https://speculativeedu.eu/approaches-methods-and-tools-for-speculative-design/>
<https://medium.com/demagsign/8-spectacular-speculative-designs-44fb129eb4e2>
5. The idea is to imagine, the good, the bad, and the ugly of MMLA - for instance how would brain implants work with Learning Analytics, what would be the ramifications across social-economic levels, or even more importantly learning self-regulation.
6. The idea is to be inspired by mood boards (https://en.wikipedia.org/wiki/Mood_board (Links to an external site.)) and future thinking in terms of ethics and privacy while considering the benefits and challenges of LA.



Outputs Expectations

- Each team elect a spokesperson(s) be prepared to discuss with everyone your group's speculative design fiction for MMLA
- Keep in mind the playful nature of this exercise and you go between utopia and dystopia
- We are playing designers, so a broad and shallow approach required instead of a deep and narrow academic view of the world.



Literature

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