

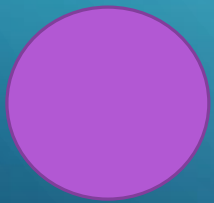
An abstract graphic on the left side of the slide, consisting of a network of white lines and circles on a blue gradient background. The lines are vertical and horizontal, with some diagonal segments, and the circles are of varying sizes, resembling a circuit board or a neural network diagram.

# BEYOND ACCURACY: SERENDIPITY

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# ACCURACY

- Tells if the recommender system is able to predict those items that you have already rated
- Accuracy will naturally place those items at the top of a user's list
- Does not take usefulness into consideration



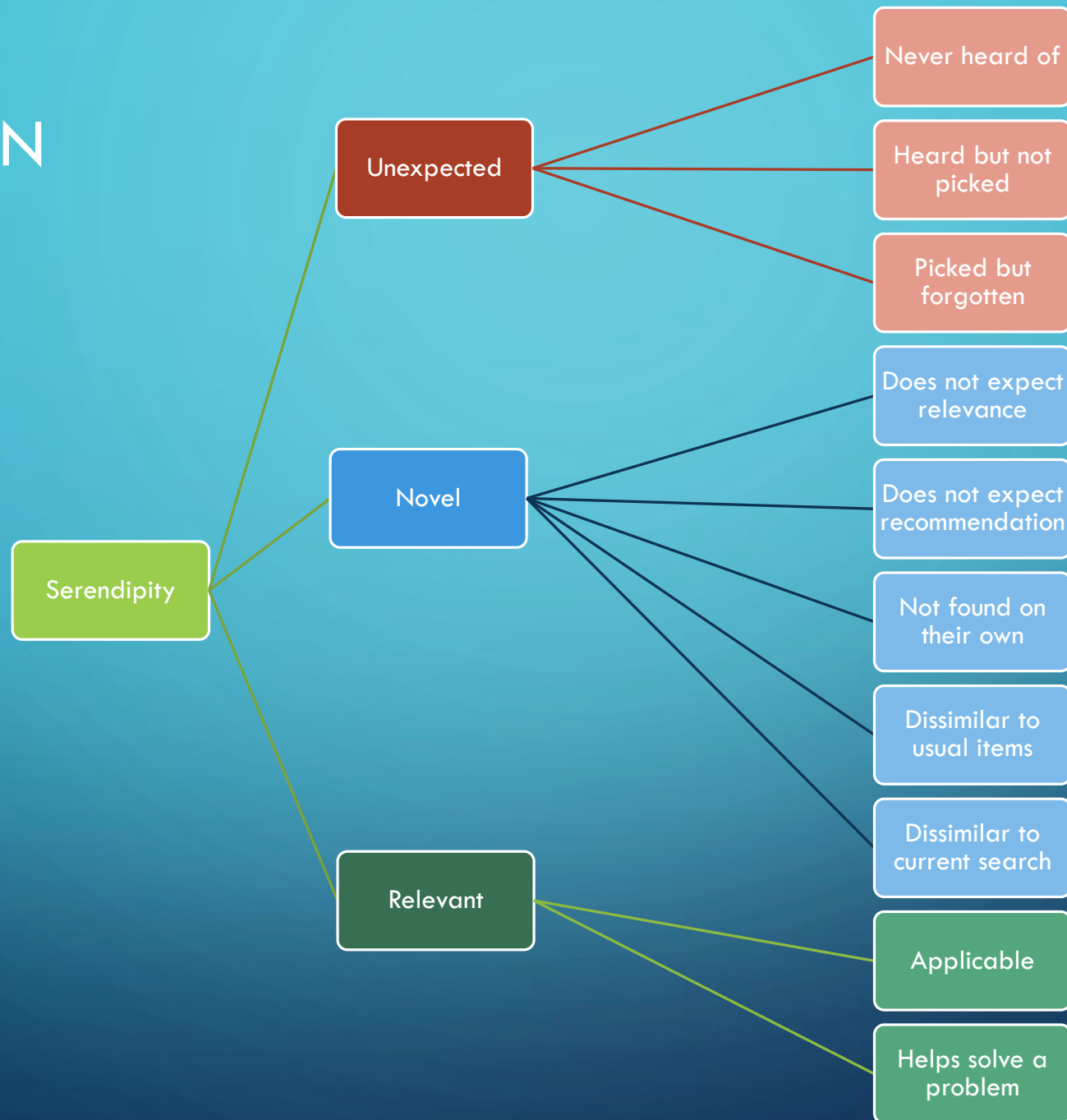
## OTHER METRICS

- Diversity — How dissimilar are the recommendations?
- Coverage — What percentage of the user-item space can be recommended?
- Relevancy — How relevant are the recommendations?
- Novelty — How surprising are the recommendations in general?
- **Serendipity — How surprisingly delightful are the relevant recommendations?**

# SERENDIPITY

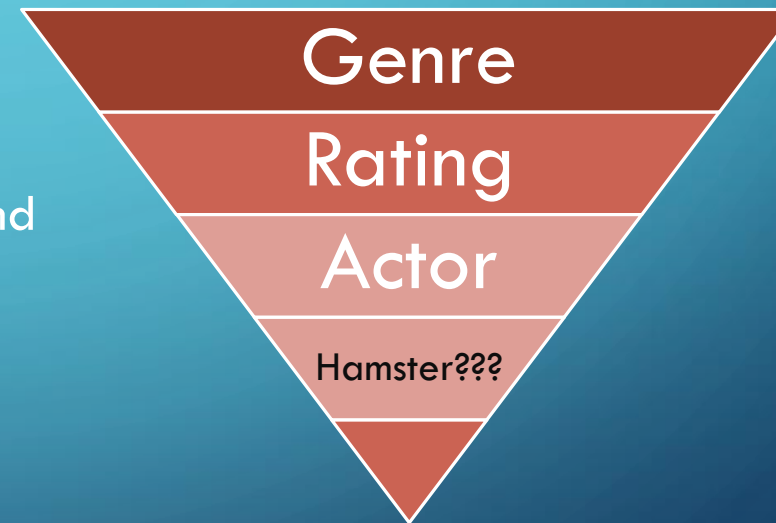
- System appears more lively by making non-trivial and surprising recommendations
- Reveals unexpressed users' wishes
- Difficult to measure
  - How do you measure levels of unexpectedness?
  - How do you measure levels of delight?
  - Ratability has its pitfalls with emotional responses
    - Emotions are unpredictable
    - The popular choice may not be picked
- Focus shift
  - Previously unimportant now is important

# DEFINITION



# STRATEGIES TO INDUCE SERENDIPITY

- Randomness
  - Introduce new items into the system
  - High Risk since randomness is not relevance
- Already existing items
  - Make recommendations based on background items
  - Focus shift is important
- Anomalies
  - Focus on items that are unexpectedly liked



	Item 1	Item 2	Item 3	Item 4
Actual	Liked	Hated	Hated	Liked
Predicted	Liked	Hated	Hated	Hated

# HOW TO SERENDIPITY

- Surprise! No one has a standard way to do this.
  - No satisfactory Collaborative Filtering solution for serendipitous item recommendation
- **Surprise/Unexpectedness**
  - Measuring an item's surprise as its distance from a set of unsurprising items
  - Difference of probability of item recommended to user and probability of item recommended to all users
- Delight
  - Favorable rating given by user



# REFERENCES

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