

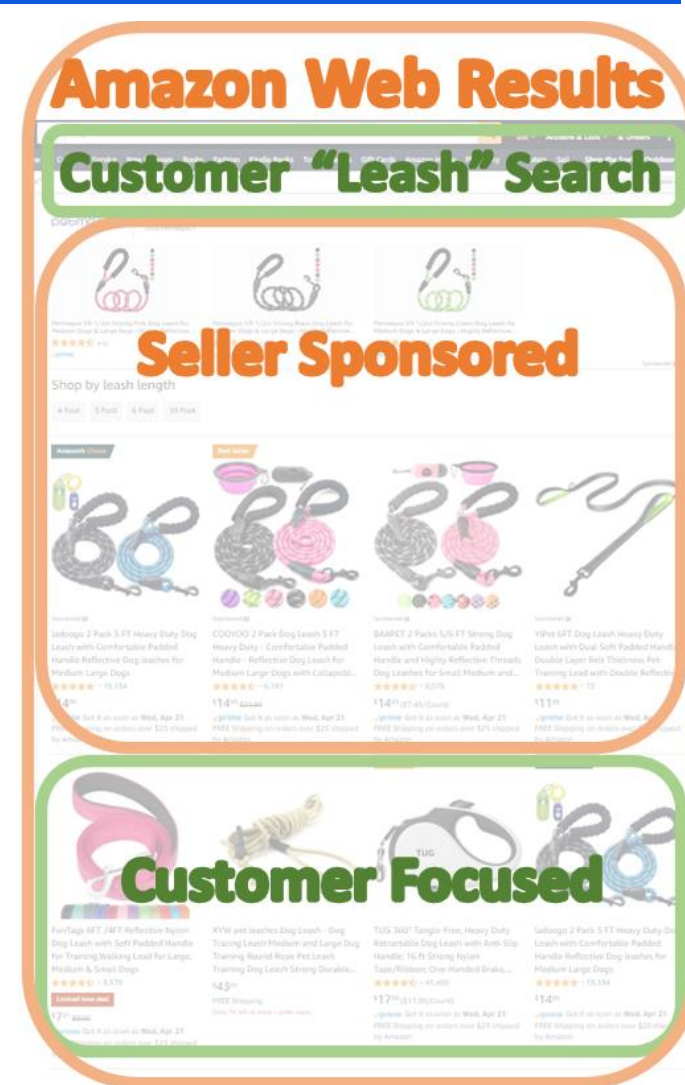


# A Multifaceted Product Recommendation System

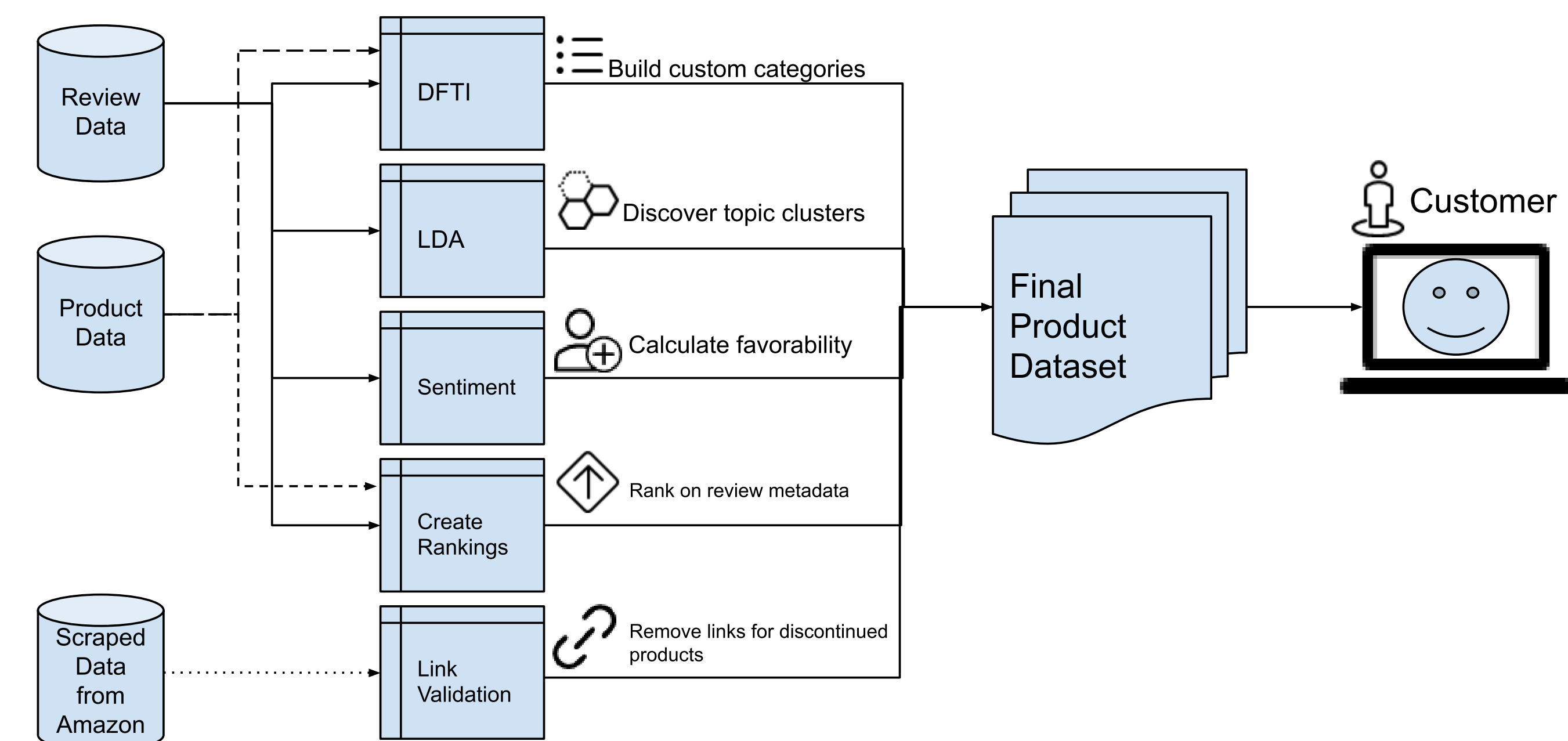
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## Motivation / Introduction

Looking on Amazon for a new toy for your pet but need some new ideas? We analyze over 6.5 million pet product reviews with multiple machine learning models and visualize the results with an interactive webpage. The goal of our project is to provide a search experience that reflects what customers think is good and not necessarily what sellers on Amazon are paying for them to see.



## Algorithms



We used four algorithms in an integrated pipeline to identify product recommendations based on customer reviews and ratings.

**Direct Frequency Topic Identification – Assign products to pet categories instead of using Amazon’s predefined categories**

A **new algorithm** developed by the team assigns each product to a category from a specific list based on keyword frequency associated with each category.

**Latent Dirichlet Allocation (LDA) Topic Analysis – Generate topic clusters from review text**

Natural language processing (NLP) along with LDA generate topic clusters. Grid search identifies optimal number of topic clusters.

**Sentiment Analysis** Sentiment score is calculated using Vader (Valence Aware Dictionary and Sentiment Reasoner) Sentiment where each review is scored and aggregated by ASIN.

**Ranking** Rank is created by product ASIN using parameters such as average rating by product, number of reviews, and average length of reviews. These parameters assess the usefulness of the review data for individual products to produce a rank for the entire dataset.

## Data Sources

**Key Stats:** 6.5 M Product Reviews | 205,999 Products

**Source:** Amazon Review Dataset. J. McCauley, UCSD.  
**5.52 GB (Downloaded)**

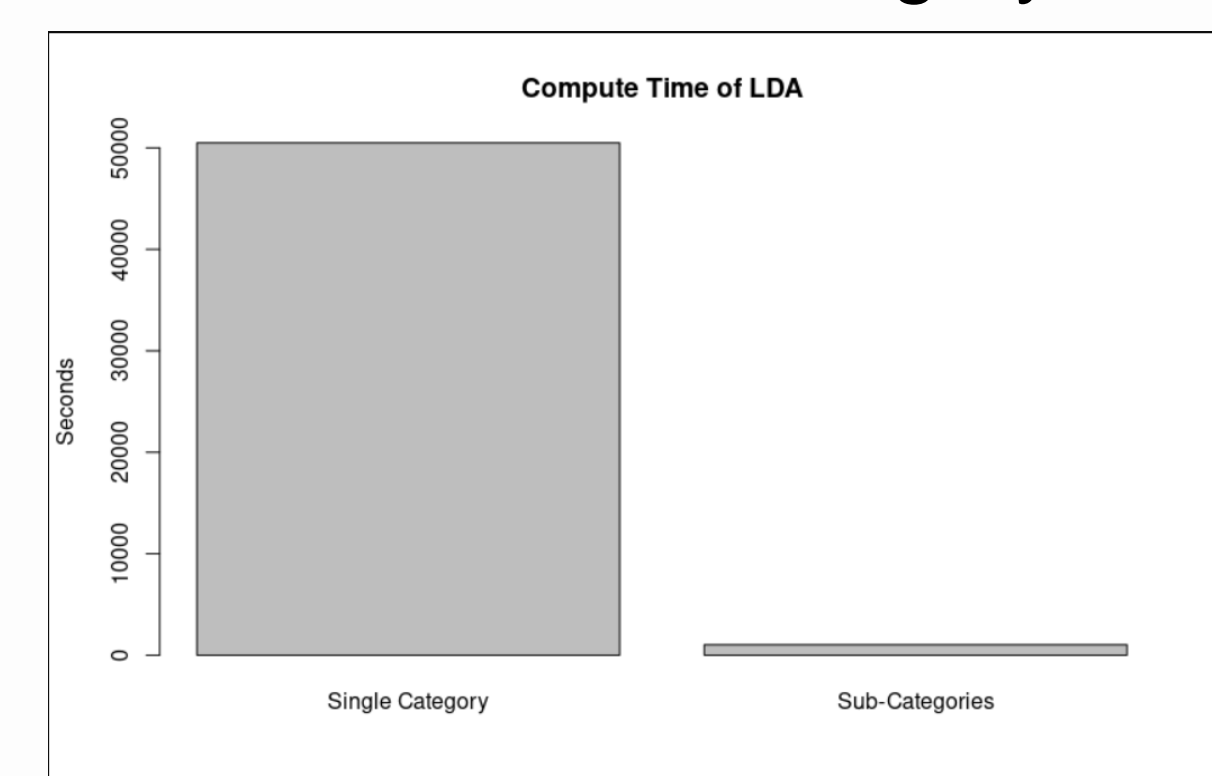
**Product review dates:** 01/08/2000 - 10/04/2018

Additional data obtained by **web scraping** Amazon.com using Selenium to validate links.

## Experiments and Results

**LDA Topic Analysis Performance – Which is more efficient, processing all reviews using LDA, or grouping all reviews into predefined categories?** We predetermined the initial category of the products (dog, cat, etc.) then used LDA to create the sub-category (topic) classifications.

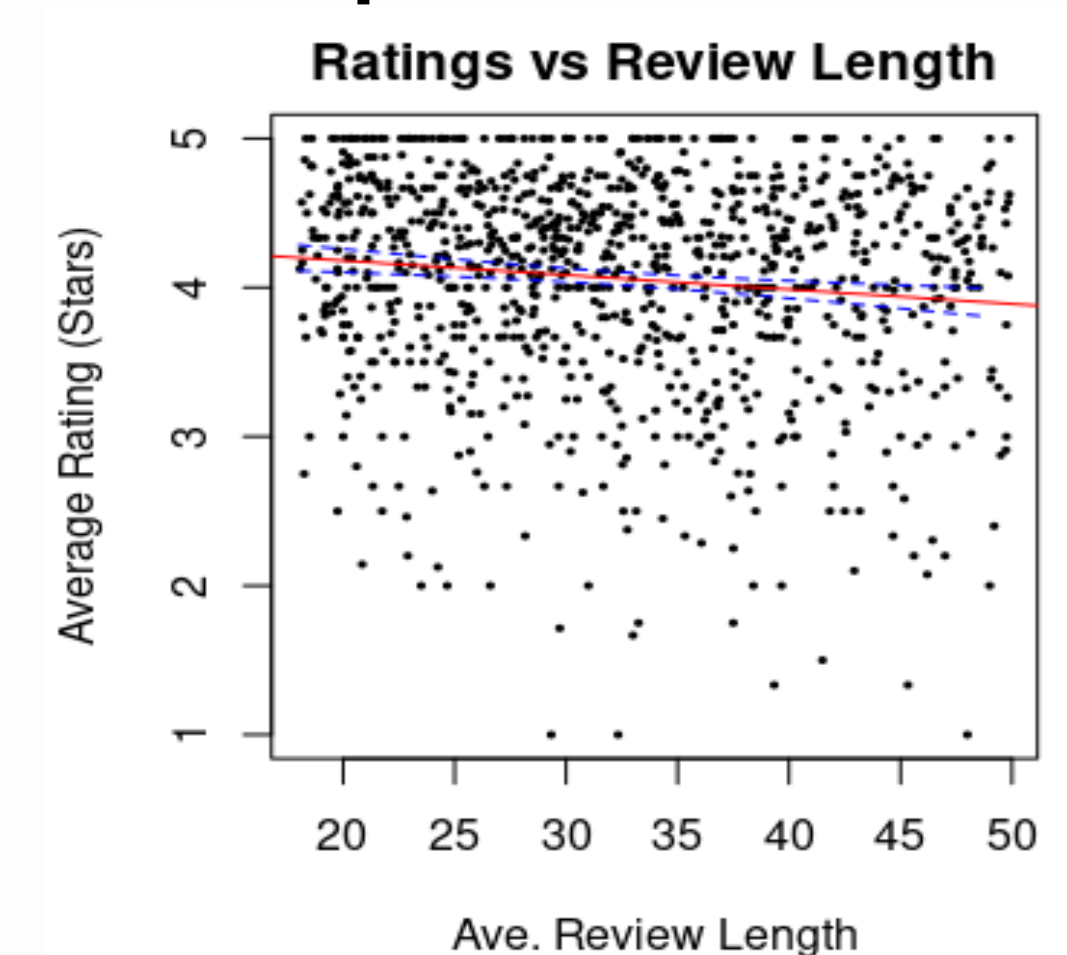
**Results:** The resulting LDA topics are more intuitive, and less computationally expensive. We reduced computation time by ~98% to 1,034 seconds (~17 min.).



**Product Rank – Does review length correlate to product ratings?**

Analysis was performed by regressing product average star ratings onto product average review length.

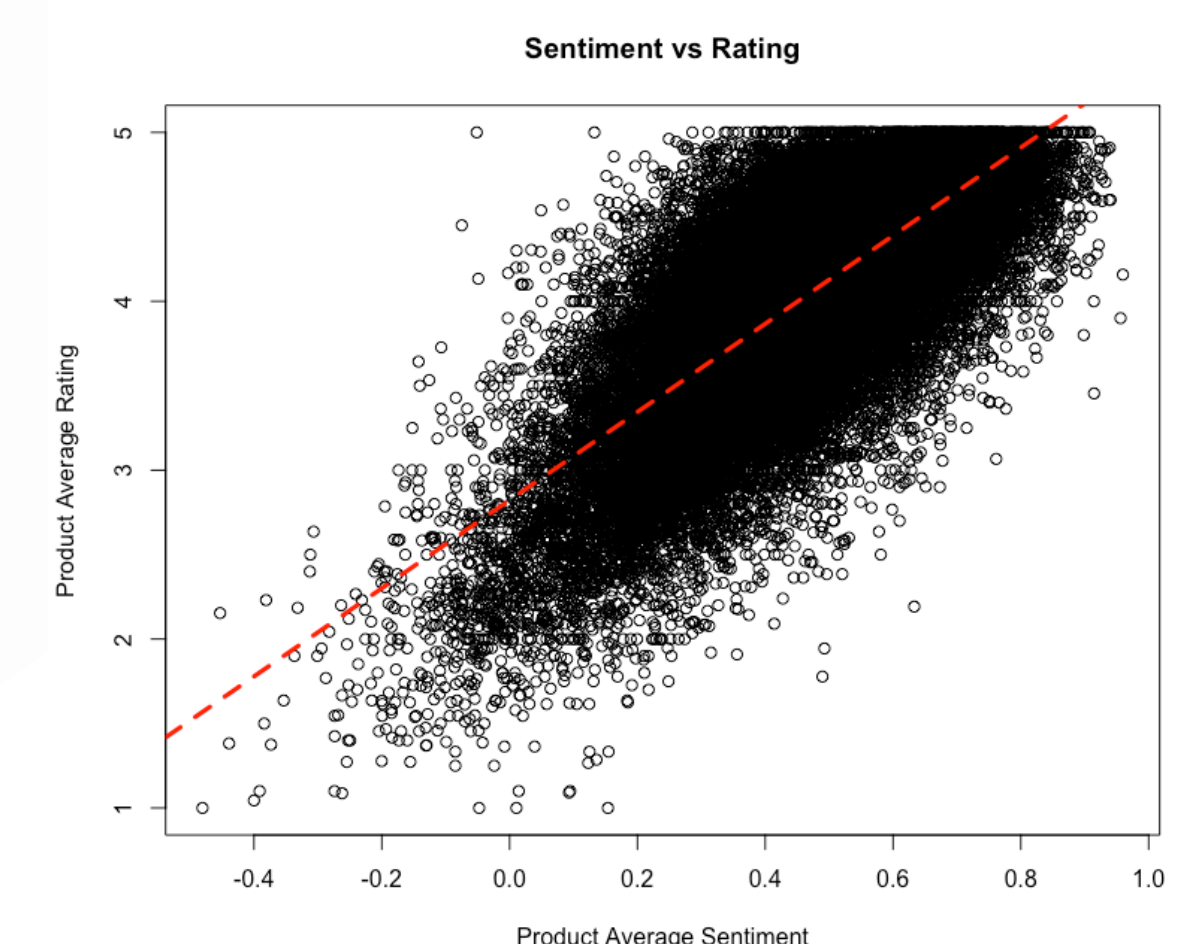
**Results:** The regression failed to show a correlation between review length and ratings.



**Sentiment – Are products with higher review sentiment**

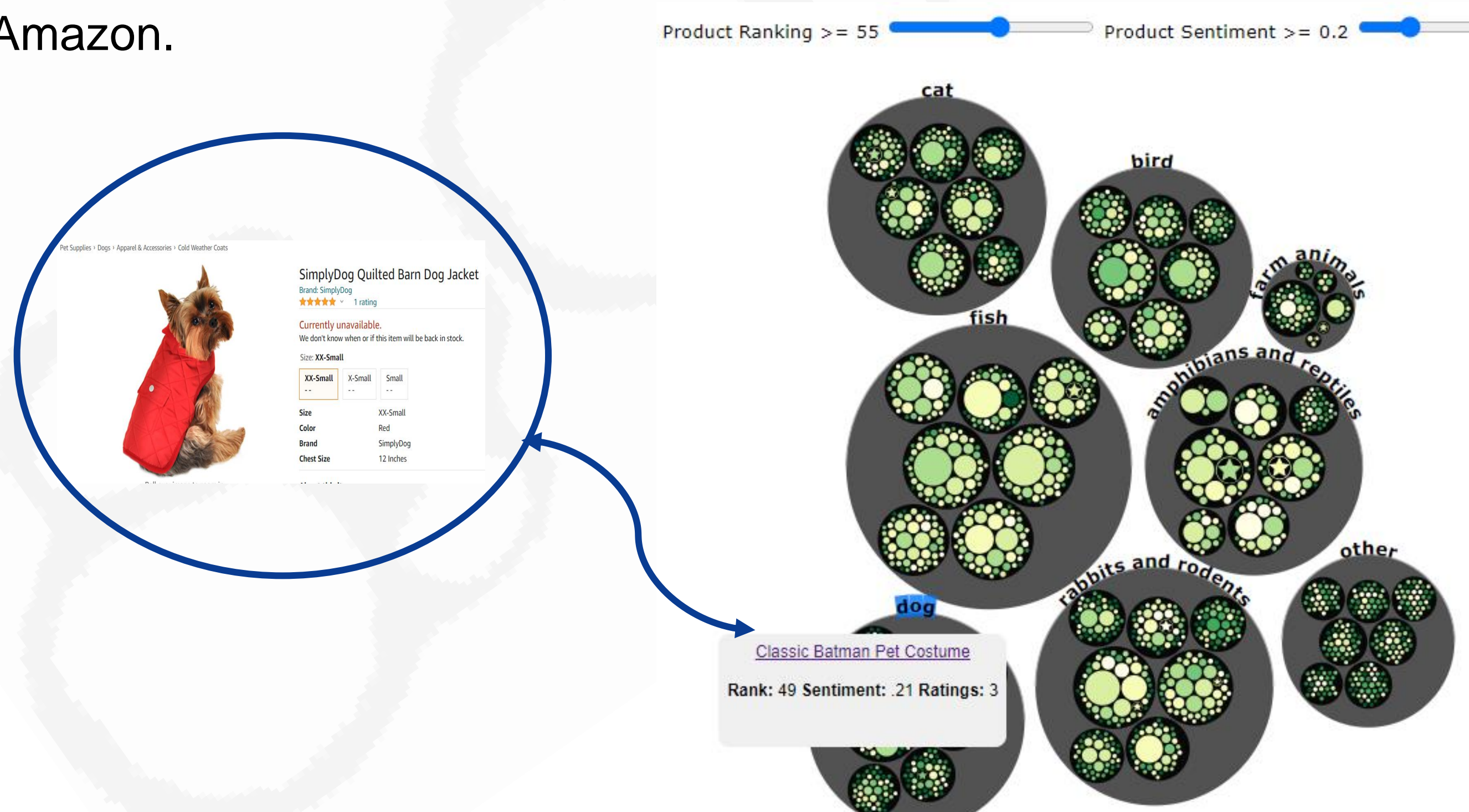
**correlated with higher product ratings?** Analysis was performed by regressing ratings onto product sentiment.

**Result:** Statistically significant ( $\alpha=0.05$ ,  $\beta=2.61$ ) positive correlation found between sentiment and rank.



## Interactive Visualization

We used a D3 interactive bubble chart to visualize pet products by topic cluster and category. Hovering on a product bubble will display a tooltip that provides product details and a link to products that are still listed on Amazon.



**Visualization Usability Experiment - Can users quickly learn to navigate the tool?**

**Experiment:**

- Users asked to perform the following task: Your neighbor has a new and you want to buy them a gift. Please use this tool to decide what you will purchase and answer the following:

**Questions / Results:**

- Does the user find a suitable recommendation within 3 minutes? Goal: 60% less than 3 minutes. **Result: 67%**
- Did the user encounter any errors? Goal: Zero mission critical user experience errors **Result: 94%**
- Rate on scale of 1 - 5: Goal: 3.5 or above  
**Result:** Helpfulness **3.6**, Usability **3.7** and Topic Relevance **3.9**
- Does it provide enough details to make a purchase, yes or no? Goal: 60% **Result: 56%**