Cultural Diffusion and Trends in Facebook Photographs

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“Culture”

• Lifestyles commonly shared by members of a society or community at a certain time.

• Food, fashion, sports, hobbies, music, ...
  • What we eat, what we wear, what we do, ...

• Distinct cultures exist.
  • Western vs. Eastern
  • They can be diffused to another culture.
Diffusion of Culture

Chinese Food

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How is culture diffused?

• Culture travels with **people** (conquerors, immigrants, workers, travelers)

• Also by **media**
  • Hollywood movies spreading American pop culture to the world – by “**seeing**”
Role of **Social Media** in Cultural Diffusion

- Can culture be diffused via social ties in online social networks?

- Can cultural preferences and lifestyles of a user be diffused to another user – by **photographs**?
Why Photographs?

- Rich information about user lifestyles.

- Often, it is a unique modality for some information
  - Other cues (text, tags, minutiae, check-ins) may not state everything in photographs.
Our Approach

• Automatically infer cultural activities or lifestyles from user photographs using deep learning.

• Then examine:
  1. Social correlation: whether tied individuals post more similar photographs
  2. Social influence: whether the similarity is due to influence (diffusion) or homophily (inherent similarity)
Cultural Concepts in Photographs

• 11 categories
• 920 visual concepts
  • Objects, events, activities, places, photographic style
• Some region-specific cultures (American Football); but covers a wide range of general human lifestyles (bicycle, dog, beer)

<table>
<thead>
<tr>
<th>Category</th>
<th>Concepts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports</td>
<td>baseball, basketball, climbing, football, golf, ski, soccer, swimming, tennis . . .</td>
</tr>
<tr>
<td>Animals</td>
<td>bear, bird, bug, cat, cow, crocodile, deer, dog, horse, spider, tiger . . .</td>
</tr>
<tr>
<td>Clothes</td>
<td>backpack, bikini, boots, dress, hat, heels, sunglasses, ties, . . .</td>
</tr>
<tr>
<td>Food</td>
<td>avocado, bagel, banana, beer, blueberry, icecream, pizza, salad, sushi . . .</td>
</tr>
<tr>
<td>Furniture</td>
<td>bookshelf, bed, chair, kitchen, table, . . .</td>
</tr>
<tr>
<td>Music</td>
<td>accordion, cello, flute, guitar, piano, . . .</td>
</tr>
<tr>
<td>Plants</td>
<td>flower, grass, trees, bush, . . .</td>
</tr>
<tr>
<td>Structures</td>
<td>bridge, house, chimney, monument, skyscraper, . . .</td>
</tr>
<tr>
<td>Places</td>
<td>Big Ben, Colosseum, Eiffel tower, Louvre, Opera House . . .</td>
</tr>
<tr>
<td>Scene</td>
<td>beach, closeup, fireworks, nature, night, selfie, sky, sunset, water, . . .</td>
</tr>
<tr>
<td>Vehicles</td>
<td>bicycle, boat, bus, car, train, . . .</td>
</tr>
</tbody>
</table>
Automated classification by a CNN

• Residual Net 50-layer (He et al. 2016)
• 920 independent binary classifications
• Hard-negative and positive example and annotations collection by active learning
• Torch
Automated classification by a CNN

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Automated classification by a CNN

<table>
<thead>
<tr>
<th>Category</th>
<th># of Concepts</th>
<th>Avg AUC</th>
<th>Avg ratio of positives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports</td>
<td>64</td>
<td>0.972</td>
<td>$1.93 \times 10^{-4}$</td>
</tr>
<tr>
<td>Animals</td>
<td>108</td>
<td>0.982</td>
<td>$3.14 \times 10^{-4}$</td>
</tr>
<tr>
<td>Clothes</td>
<td>88</td>
<td>0.882</td>
<td>$1.71 \times 10^{-3}$</td>
</tr>
<tr>
<td>Food</td>
<td>107</td>
<td>0.979</td>
<td>$2.56 \times 10^{-4}$</td>
</tr>
<tr>
<td>Furniture</td>
<td>38</td>
<td>0.942</td>
<td>$5.52 \times 10^{-4}$</td>
</tr>
<tr>
<td>Music</td>
<td>16</td>
<td>0.983</td>
<td>$1.30 \times 10^{-4}$</td>
</tr>
<tr>
<td>Plants</td>
<td>33</td>
<td>0.954</td>
<td>$2.36 \times 10^{-3}$</td>
</tr>
<tr>
<td>Structures</td>
<td>17</td>
<td>0.973</td>
<td>$8.33 \times 10^{-4}$</td>
</tr>
<tr>
<td>Places</td>
<td>73</td>
<td>1.000</td>
<td>$6.03 \times 10^{-6}$</td>
</tr>
<tr>
<td>Scenes</td>
<td>113</td>
<td>0.923</td>
<td>$1.41 \times 10^{-3}$</td>
</tr>
<tr>
<td>Vehicles</td>
<td>53</td>
<td>0.978</td>
<td>$6.55 \times 10^{-4}$</td>
</tr>
</tbody>
</table>
What’s popular – Sports

Snowboarding

Surfing

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What’s popular – Food

Sushi

Taco

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Trends

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Social Correlation

• Correlation between cultural lifestyles of tied individuals (friends)
• Are friends more likely to post photographs that exhibit similar cultural lifestyles?
• Measured by the difference of cosine similarities of CNN outputs between friend and non-friend pairs.

\[
D_{corr}(T) = \frac{1}{|T|} \sum_{(v_i, v_j, v_k) \in T} \cos(x_i, x_j) - \cos(x_i, x_k).
\]

- \(x_i\): a user,
- \(x_j\): a friend,
- \(x_k\): a random non-friend user,
  of the same gender & age group as \(x_j\)

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Social Correlation

• Dataset
  • 1.3 M users
  • 250 M photographs, 2013-2016
  • Seattle area – the same location

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Social Correlation

• All statistically significant (p-val < 0.00001) except Music (p-val = 0.111).
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Social Influence

• Influence vs. Homophily
  • Influence: cultural lifestyles can be diffused via friendship ties.
  • Homophily: people with similar lifestyles are more likely to become friends.

• Predictive influence
  • Observational data
  • Shuffle Test (Anagnostopoulos, Kumar & Mahdian 08)
  • PME Test (Sharma & Cosley 16)
Shuffle Test

• Measure correlations before/after permuting the timestamps associated with user photographs.
• Idea – the temporal propagation of a visual concept would be aligned with the friendship ties if there was an effect of influence.
Shuffle Test

• Correlation between (via logistic regression)
  • # of friends who post about a visual concept and,
  • Whether the user will also post the same concept or not
Shuffle Test

• Overall, correlations were reduced after permutation: the effect of influence

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### Shuffle Test

<table>
<thead>
<tr>
<th>Concept</th>
<th>Shuffled</th>
<th>Original</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>face</td>
<td>0.18</td>
<td>0.416</td>
<td>0.236</td>
</tr>
<tr>
<td>person</td>
<td>0.185</td>
<td>0.411</td>
<td>0.226</td>
</tr>
<tr>
<td>child</td>
<td>0.18</td>
<td>0.389</td>
<td>0.209</td>
</tr>
<tr>
<td>smiling</td>
<td>0.179</td>
<td>0.383</td>
<td>0.204</td>
</tr>
<tr>
<td>table</td>
<td>0.179</td>
<td>0.381</td>
<td>0.202</td>
</tr>
<tr>
<td>tree</td>
<td>0.196</td>
<td>0.393</td>
<td>0.197</td>
</tr>
<tr>
<td>night</td>
<td>0.176</td>
<td>0.371</td>
<td>0.195</td>
</tr>
<tr>
<td>sky</td>
<td>0.2</td>
<td>0.395</td>
<td>0.195</td>
</tr>
<tr>
<td>pants</td>
<td>0.2</td>
<td>0.393</td>
<td>0.193</td>
</tr>
<tr>
<td>hug</td>
<td>0.187</td>
<td>0.374</td>
<td>0.187</td>
</tr>
<tr>
<td>shoes</td>
<td>0.206</td>
<td>0.393</td>
<td>0.187</td>
</tr>
<tr>
<td>plant</td>
<td>0.214</td>
<td>0.392</td>
<td>0.178</td>
</tr>
<tr>
<td>drink</td>
<td>0.21</td>
<td>0.374</td>
<td>0.164</td>
</tr>
<tr>
<td>restaurant</td>
<td>0.202</td>
<td>0.36</td>
<td>0.158</td>
</tr>
<tr>
<td>hat</td>
<td>0.221</td>
<td>0.379</td>
<td>0.158</td>
</tr>
</tbody>
</table>

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PME Test

• Preference-based Matched Estimation (Sharma & Cosley 2016)
• At time $t$, sample a network:

\[ J(f, s) = \frac{|A_t^f \cap A_t^s|}{|A_t^f \cup A_t^s|} \]

\[ N(f, s) = \frac{|A_t^f| - |A_t^s|}{|A_t^f|} \]

Sample a non-friend user who is similar to $f$

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PME Test

- Preference-based Matched Estimation (Sharma & Cosley 2016)
- At time $t+1$, compare two similarities:

$$\text{Inf}(u) = \frac{\sum_{c \in A_{t+1}^{F(u)}} I(c \in A_{t+1}^u)}{|A_{t+1}^{F(u)}|} - \frac{\sum_{c \in A_{t+1}^{S(u)}} I(c \in A_{t+1}^u)}{|A_{t+1}^{S(u)}|}$$

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PME Test

• The original network has a higher similarity (between true friend pairs).

• Effect of influence

<table>
<thead>
<tr>
<th>Influence</th>
<th>std</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.07</td>
<td>0.09</td>
<td>293</td>
<td>&lt; 10^{-5}</td>
</tr>
</tbody>
</table>
Discussions

• Social media can offer a channel for cultural exchanges via exposures to user content between online friends.

• Our study finds the effect of influence using photos.
  • User tagging has been reported as non-influential in other platforms: flickr (Anagnostopoulos, Kumar & Mahdian 2008), Flixster, Last.fm, Goodreads, flickr (Sharma & Cosley 2016).
Discussions

• Limitations
  • Observational study
  • Only visual analysis

• People communicate via visual means in social media. Photographs are a great channel to understand their behaviors.