PopNet: a Pop Culture Knowledge Association Network for Supporting Creative Connections

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Fig. 1. Star Wars Day creative visuals collected on Twitter from (a) McDonald’s, (b) Volkswagen, and (c) Girl Scouts

Pop culture is a pervasive and important aspect of communication and self-expression. When people wish to communicate using pop culture references, they need to find connections between their message and the things, people, location and actions of a movie, tv series, or other pop culture domain. However, finding an appropriate match from memory is challenging and search engines are not specific enough to the task. Often domain-specific knowledge graphs provide the structure, specificity and search capabilities that people need. We introduce PopNet - a Pop Culture Knowledge Association Network automatically created from plain text using state-of-the art NLP methods to extract entities and actions from text summaries of movies and tv shows. The interface allows people to browse and search the entries to find connections. We conduct a study showing that this system is accurate and helpful for finding multiple connections between a message and a pop culture domain.

CCS Concepts: • Human-centered computing → Interactive systems and tools.

Additional Key Words and Phrases: popular culture, knowledge graphs, associations, creativity, connections

ACM Reference Format:
Sitong Wang and Lydia B. Chilton. 2021. PopNet: a Pop Culture Knowledge Association Network for Supporting Creative Connections. In . ACM, New York, NY, USA, 13 pages.

1 INTRODUCTION

Pop culture is an important aspect of communication. References to memorable moments in television, film, and other mediums pervade internet communication as well as everyday conversation. Creative messaging often leverages
connections between the user’s topic and pop culture. For example, on Star Wars Day many organizations form connections between their messages and Star Wars and create an image to post on social media. This is done by companies like BMW, government organizations like NASA, nonprofits like The Met Museum and the Girl Scouts of America. It is done for many pop culture domains, particularly when a new season of a show begins. No matter what the organization or pop culture domain, they seem to be able to find creative ways to link their message to the domain.

When creating an image with pop culture references, there are two challenges: finding a domain-related entity or action that connects to the message, and then finding associated entities to “fill the scene” and enhance the message. To find a good match, it is helpful to find many possible options for the user to search and browse. To fill the scene, it is helpful to know associated entities and actions to select. This could be objects, people, locations, organizations, and actions from the pop culture domain. In creativity, these steps are called divergent and convergent thinking. Divergent thinking is often difficult because it requires users to recall multiple things from memory. Convergent thinking is difficult because it requires trying multiple combinations to meet the constraints of the problem.

To address the challenges of divergent and convergent thinking in creating pop culture connections, we present PopNet - a knowledge association network listing entities and associations within a given pop culture domain. For example, given Star Wars movies 4, 5, and 6 as a pop culture domain, it extracts the entities (people, locations, organizations, and objects) and actions of those movies. Beyond being simply a database or a knowledge graph, we identify the common associations between the entities and present canonical images for each of them. PopNet uses plain text plot summaries from Wikipedia, and uses state-of-the-art Natural Language Processing to construct a knowledge graph. It then further processes the summaries for co-occurrence data to determine associations between entities and their strengths. Although knowledge bases and association networks exist for general information, to our knowledge this is the first knowledge base or association network with rich pop culture knowledge. Additionally, although there is a wealth of pop culture knowledge on fan-created wikis, it is not structured in ways that support finding creative connections.

This paper makes the following contributions:

- PopNet: a knowledge association network for pop culture domains which is automatically created from plain text plot summaries.
- An interface that allows users to search and browse PopNet within a domain to support divergent and convergent thinking.
- An evaluation showing the users prefer using PopNet to web search when making PopRef images.

We conclude with a discussion of how to extend this work to other forms of pop culture and how knowledge association networks can support finding connections in other creative tasks.

2 TASK: POPREF IMAGES

Although pop culture references are pervasive, to investigate supporting creative connections to pop culture we focus on a single task. The task we chose is to create images for a message with multiple references to a single pop culture domain. We call these PopRef images. Figure 1 shows three examples of PopRef images for the Star Wars domain. They are all advertisements posted on May 4 for “Star Wars Day.” Diverse companies like McDonald’s, Volkswagon and The Girl Scouts of America were each able to produce a different image that relates to their products.

A key challenge in this task is to have multiple, cohesive references to the a single domain. For example, in the McDonald’s ad, the image references Luke’s hand pulling a lightsaber out of snow on the planet Hoth. Likewise, the
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Volkswagen ad has references to Han Solo, Chewbacca, the Millennium Falcon. In the ad for Girl Scout Cookies, Luke and Darth Vader are fighting with lightsabers. Although it is possible to use only a single reference, the images seem more clever when there are multiple cohesive connections.

This task is related to visual metaphors [17, 52] a commonly studied creative design challenge and which several systems support creating [12, 13, 28]. It does blend ideas from two domains into single image to express new meaning but it does not strictly need to be a metaphor - any connection is fine. Unlike visual metaphors, PopRef images must have multiple connections to the pop culture domain.

3 RELATED WORK

3.1 Knowledge Graphs and Association Data

Knowledge graphs are a powerful tool for accessing structured information. They are often used by search engines and question answering services to deliver direct responses to users queries for facts about the world. From 2016-2020, interest in domain-specific knowledge graphs has increased dramatically with many applications in Health, Education, Telecommunications, Science and Business [1]. One potential reason for this increase is advances in NLP [20] that enable automatically constructing high quality knowledge graphs. Creating and maintaining knowledge bases by hand is often prohibitively expensive. But the potential to do it automatically makes opens many new applications.

Existing knowledge graphs cover a broad range of human knowledge, but do not cover popular culture in any reasonable depth. WordNet [39] and ConceptNet [35] are wildly used knowledge graphs, but focus almost exclusively on words in the dictionary, which excludes popular culture. Databases like DBPedia [7] cover everything in Wikipedia and thus do have pop culture entries, but the focus is on facts about entities in movies, rather than the role they play in the movie. Google Knowledge Graph has pop culture knowledge, but has uneven coverage for pop culture; it has entries for “characters in Friends” but not in Star Wars or Game of Thrones. Fan-created wikis for pop culture domains do contain a massive amount of entities. However, the focus is on creating articles for people to read and the meta data and other structured information is not always complete or useful.

Like knowledge graphs, association networks store related entities or concepts, however unlike knowledge graphs, the only link between the entities is how closely associated they are. A high quality source of associations is Small World of Words [14] - a crowdsourced dataset of word associations. Unfortunately, this association data set and others like WordAssociations.net tend to have little or no popular culture entities in them. Word embeddings [38, 41] are a potential source of word associations that could be generated automatically. Word embeddings trained on internet corpuses often have popular culture entities in them, however, there is no guarantee of coverage. Moreover, human evaluations show that the contents of word associations dataset produce more related and similar words than word embeddings, and more closely match our “mental lexicon.” [15]. A common way of producing associations is to calculate at co-occurrence within a given window size [18, 50, 60]. For PopNet, we found this was a simple and reliable source of automatically generating associations within our knowledge graph.

3.2 Supporting connections in creativity

Psychologists consider association an essential part of the creative process [36]. The famous mathematician Poincare posited that “to create consists of making new combinations by providing mediating connective links”. This insight is captured in the popular model of creativity as being divided into divergent thinking and convergent thinking [51]. During divergent phase, the goal is to come up with many possible useful pieces. During the convergent phase, those
pieces come together in ways that achieve the goal. These phase are used together in many combinations to perform creative work and problem solving [16]. They are both difficult tasks that can be supported with computational tools.

Divergent thinking is difficult because it requires recalling multiple diverse associations from memory. Knowledge graphs are commonly used to present text inspiration. InspirationWall [5] is a brainstorming support system that presents a related topics from a knowledge graph. Spinneret [8] helps people build mind maps with non-obvious associations from ConceptNet. Metaphoria [21] helps people make metaphorical connections using ConceptNet and ranking the results with word embeddings. Other approaches to presenting text inspiration are to use word embeddings [31], association data [28, 43], or a real-time crowd [6, 48]. Presenting images to users during a brainstorm can further spur associations [47, 53] and those image can be optimized for preference [32] or adapted to cultural context [54]. All these approaches are valid and helpful for supporting divergent thinking. In PopNet combine three of these approaches - knowledge graphs, associations and images to help people find ideas.

Convergent thinking is difficult because it requires synthesizing many pieces of information into a cohesive output. Creative design tasks are ill defined, and thus there is no exact formula to converge on a solution, but there are several ways to help ease the cognitive load. Rapid prototyping tools [12, 24, 25, 56] create a layer of abstraction over low level hardware or software details to help users focus on the combining the ideas rather than fiddling with mechanics. They also present an environment where all the tools are ready-to-hand. In design, having a well-curated environment is sometimes called mise-en-place [40, 55]. When there are known constraints for a solution, software systems can help search the parts to find combinations that meet the constraints [2–4, 33, 37] or adhere to expert design principles [13, 27, 29, 46, 61] or schemas [22, 26]. When computational approaches fail, crowd workflows can be constructed to guide worker to do recombination [59], analogical reasoning [57, 58], or synthesis [11, 30, 45]. For the PopRef Image task, it is easiest to see it as a problem with multiple constraints - the user must find multiple references to a pop culture domain that all go together cohesively. To support people making these connections we offer two solutions: 1) semantic search to automatically search the database to find an initial reference, and 2) an environment with structured and associative links ready-to-hand for finding related entities to fill the scene.

4 POPNET SYSTEM

For PopNet we combine structured knowledge with associations to generate a network then can be easily explored for creative tasks. Based on a survey of research on creating knowledge graphs, there is a generally accepted way of using NLP to construct knowledge graphs from plain text [1]. First parse the text into sentences. Second, use Named Entity Recognition (NER) to extract entities and their types. Third, use Information Extraction (IE) to find links. Lastly, store the links as triplets. Sometimes, co-reference resolution is advised before NER and IE. Sometimes dependency parsing is recommended to extract non-named entities, although it becomes complicated to extract entities from their surrounding noun phrase. For PopNet, we follow these steps, using Wikipedia plot summaries as the input text, using AllenNLP [19] as a source of high quality NER and IE, and we opt to use conference resolution before NER and IE. Details about each step are as follows.

4.1 Knowledge Association Network Creation

4.1.1 Input Data Collection. We scrape plot sections in pop culture domains’ wiki page(s) (e.g., Star Wars trilogy, Game of Thrones season 1-8) as the data resource. Data from wiki pages have advantages of being generalizable, updated and relatively structured. We choose the plot section to scrape because plot is “a narrative sequence of events that determine the outcome of the character”, which in other words, is a concise expression covering most entities and their
important events. We also consider other alternatives including 1) Fandom wiki pages, which are compiled by fans and cover many pop culture domains but being highly unstructured and too detailed; 2) Small World of Words and ConceptNet, which can associate specific entities to a domain, but barely having nothing for the pop culture domain; 3) Google knowledge graph, which lets users find richer meaning about a concept, but currently having nothing for a specific pop culture domain either.

4.1.2 Entity Extraction (Nodes). We then extract entities based on the scraped plot sections. To extract entities from the plot text, we first run ELMo-based named entity recognition model to get named entities ("referents of proper nouns and other noun phrases") with tags of people, organizations, locations and miscellaneous, which are a large part of entities we want. ELMo-based model achieves 99% accuracy and 96% F1 on the CoNLL-2003 validation set [42]. However, we also want non-named entities such as lightsabers in Star Wars and dragons in Game of Thrones, and we do it with a different approach. Using an extra 100 random wiki pages as the corpus, we run the TF-IDF method to extract non-named entities. TF-IDF is a common technique to statically extract important (frequent in the domain and rare in others) vocabularies for a domain document. After that, we merge the named and non-named entities, and finally get the entity list for the pop culture domain.

4.1.3 Entity Association and Action Extraction (Edges). Based on the entity list, we then want to figure out associations between these entities. To start with, we target entity pairs co-occurring in the same sentence of the plot, because entities showing in one sentence are highly likely to appear in the same event, which means being highly related. Before finding co-occurring entity pairs, we take a pre-processing step of co-reference resolution, which means replacing pronouns in the plot with specific entity names. This step is aimed at preventing associations from being ignored because of non-specific pronouns. We run SpanBERT embedding model [34] provided on AllenNLP to achieve this goal. Then we extract the entity pairs co-occurring in the same sentence based on the text after co-reference resolution.

Now that we have co-occurring entity pairs as associative nodes, we want to further investigate what relationships are between them. We use open information extraction (open IE) model for this task to break complex plot sentences into a list of propositions, each composed of a single predicate and some arguments. If one entity is in ARG0 and another is in ARG1 of the predicate, we consider predicate (verb / action) here as the linkage between the two entities. In other words, we extract subject-verb-object relations with both subject and object being entities in our list. The BiLSTM model from AllenNLP [49] is used to automatically complete the open IE.

4.1.4 Entity Ranking and Image Collection. Following the three steps above, a knowledge association graph has been constructed for the pop culture domain. However, to make it easier for users to explore, we need to collect extra information. Some pop culture domains, such as Game of Thrones, have a large number of entities in their stories. It will be difficult for a user to explore the network if the entities (nodes) are shown in a random order. Thus we consider ranking the entities based on their "importance" or "popularity". We first consider using page count of the entity’s Google search result as the measure of their popularity. However, we find this approach not reliable for pop culture domains with real-world scenarios, especially for the ranking of characters. For example, with aim of finding the "popularity" of David (a supporting character in Friends), we searched "Friends + David" in Google and ended up with a surprisingly high page number. It did not improve after we added "TV show" as another constraint keyword, and it is because one of the main character’s actor is also named David and has a high popularity. To find a more generalizable way, we return to plot texts we have (with co-references resolved) and use TF-IDF approach (as we did to extract
non-named entities) to rank the entities. It is a simple but relatively reliable way to sort the entities, as the frequently mentioned entities in the domain (and rare in other random wiki pages) have their place in the movie or TV show.

To give users more information beyond just texts of entity names and actions, related images are scraped from Google Image API with certain keywords. We scrape entity images with the keyword of “[pop culture domain name] + [entity name]”. We also scrape images for entity pairs with the keyword of “[pop culture name] + [entity1 name] + [entity2 name] + scene”. We add the keyword “scene” because we find this combination is most likely to get related images, after experiments with other candidates such as “moment” and “shot”.

4.2 PopNet Interface for Browsing and Semantic Search

We implement a simple interface for users to explore the knowledge association network we built in the previous section. The interface mainly contains three levels of pages - overview page, association page and detailed page. A BERT-powered semantic search bar is also added for better exploration.

4.2.1 Overview Page. The overview page has five rows, each representing one category in the knowledge association network, which are namely people, organizations, locations, objects (others) and actions. Entries of each row are sorted and tagged with their name and ranking within the type. Entity images are shown as intuitive visual cues and are clickable as the entrance to next level - association page. Actions row are supplemented with subject-verb-object phrases, where entities are tagged with the hyperlink to their association page.

4.2.2 Association Page. Each entity in the knowledge network has their own association page. The association page first shows more pictures of the entity, and then with the same structure of overview page, shows entities and actions related to this entity under different types, which are ranked with their linkage strength. Entity pair images are shown as intuitive visual cues and are clickable as the entrance to third level - detailed page. Detailed page simply shows more pictures of entity pairs and the sentences that the two entities are co-occurring with actions highlighted. This page is aimed to giving users more details if they cannot recall what happens between the entity pair they choose.
4.2.3 Semantic Search. To enhance the exploration experience of PopNet interface, we add a semantic search bar at the right corner of each page. The search bar is powered by the Siamese BERT-Networks [44], which efficiently creates BERT embeddings for queries and source sentences, as well as performs fast distance calculation for semantic search. We use two types of data as the source sentences: 1) entity names and 2) subject verb object phrases we have through the domain. As the user puts in query keyword(s), PopNet will search through both types of source sentences and return top five results (with matching percentage and category tag) for each. We also add exact matching of keyword on top of this network with sentences in the plot summaries.

5 EVALUATION

5.1 Methodology

We recruited 10 graduate students (5 female and 5 male, with an average age of 24.0, all design novices) via email and word-of-mouth in a local university. The criterion was that participants were familiar with at least one of the pop culture domains we provided. They were asked to pick one domain of their favorite to use in the study. Distribution of their choice ended up with Harry Potter (3; P1, P2 and P4), Game of Thrones (2; P9 and P10), Friends (3; P3, P7 and P8) and Breaking Bad (2; P5 and P6), covering movies and TV shows with fictional or real-world settings.

During the experiment, each participant was asked to make PopRef images for four topics related to a product or PSA: 1) Oreo cookie; 2) BMW car; 3) Eat vegetables; 4) Wash your hands. By using PopNet or Baseline, they were required to use references from the pop culture domain of their choice to convey the topics. Basic concepts of PopRef image design and PopNet usage were introduced with an Star Wars example by one of the researchers. During the 10 minutes of ideating for each topic, participants were given a notepad to record their ideas and encouraged to think of as many ideas as possible. After the task session, participants completed a questionnaire that covered NASA-TLX [23], creativity support index [10], and use of PopNet features. A 10-min semi-constructed interview was followed right after to collect comments regarding their experience. In the end, participants were asked to make a slide for each of their ideas, which should contain a tagline and some images arranged to "get the point" of what pop culture reference they use to convey the topic. Once they finished with the slides, the whole process ended.

In terms of the order of using systems, the 10 users were evenly grouped into two combinations: 1) Oreo cookie (Baseline) - BMW car (PopNet) - Eat vegetables (Baseline) - Wash your hands (PopNet) and 2) Oreo cookie (PopNet) - BMW car (Baseline) - Eat vegetables (PopNet) - Wash your hands (Baseline). We chose Google search as our baseline as it is commonly used by designers to do creative tasks.

5.2 Results

5.2.1 Workload Estimates of Making PopRef Images with PopNet and Google. NASA-TLX is a standard scale to obtain workload estimates of task performers, measuring from dimensions of mental demand, physical demand, temporal demand, performance, effort and frustration [23]. With Google search engine as baseline, we hypothesize that users find PopNet easier to use during the PopRef image design tasks. Results of the NASA-TLX questionnaire are shown in Table 1. Users felt they performed very significantly better with PopNet than with Google, reporting an average value of performance of 2.40 with PopNet and 3.30 with Google ($t = 3.52, p = .003$). By browsing and searching the domain-specific knowledge network, users more successfully found associations they needed to "fill the scene", achieving the main goal of the PopRef image tasks. Also, mental demand ($t = 3.17, p = .029$), effort ($t = 2.39, p = .020$) and frustration ($t = 2.03, p = .037$) were significantly lower for PopNet compared to Google. As observed in the Google case, users had
Table 1. NASA-TLX questionnaire results with PopNet and Google, where the p-values (−: \(p > .100\), +: \(.050 < p < .100\), \(\ast\): \(p < .050\), \(\ast\ast\): \(p < .010\), \(\ast\ast\ast\): \(p < .001\)) are reported. Smaller value means lower task load in the dimension.

|                      | PopNet Mean | SD | Google Mean | SD | p  | Sig. |
|----------------------|-------------|----|-------------|----|----|------|
| Mental Demand        | 3.95        | 2.19 | 5.90        | 2.17 | .029 | \(\ast\) |
| Physical Demand      | 3.00        | 3.30 | 3.20        | 2.86 | .382 | -    |
| Temporal Demand      | 3.00        | 2.43 | 4.35        | 2.80 | .038 | \(\ast\) |
| Performance          | 2.40        | 1.09 | 3.30        | 1.47 | .003 | \(\ast\ast\) |
| Effort               | 3.75        | 2.37 | 5.30        | 1.63 | .020 | \(\ast\) |
| Frustration          | 1.70        | 1.84 | 3.25        | 2.73 | .037 | \(\ast\) |

Table 2. Creativity Support Index questionnaire results with PopNet and Google, where the p-values (−: \(p > .100\), +: \(.050 < p < .100\), \(\ast\): \(p < .050\), \(\ast\ast\): \(p < .010\), \(\ast\ast\ast\): \(p < .001\)) are reported.

|                      | PopNet Mean | SD | Google Mean | SD | p  | Sig. |
|----------------------|-------------|----|-------------|----|----|------|
| Enjoyment            | 13.60       | 2.07 | 12.70       | 3.80 | .232 | -    |
| Exploration          | 15.40       | 2.63 | 11.20       | 4.10 | .015 | \(\ast\) |
| Expressiveness       | 13.60       | 1.78 | 11.10       | 3.10 | .047 | \(\ast\) |
| Immersion            | 10.00       | 4.88 | 9.70        | 5.08 | .412 | -    |
| Results Worth Effort | 15.50       | 2.22 | 12.70       | 2.41 | .020 | \(\ast\) |

to come up with keywords themselves, and often needed to deal with much non-domain related information if the keyword was not carefully considered (e.g., when users searched “friends + car”, many pictures of driving happily with friends appeared, but none of them were related to the TV show Friends). Google results with low relevance often brought a dead end to users’ ideas, making them feel frustrated. On the contrary, PopNet “provides information with higher information-noise rate” (P10), decreasing lots of burden from the user side. Similarly, temporal demand (\(t = 2.01, p = .038\)) was significantly lower for PopNet compared to Google. This was likely because it often took more time for users to browse and filter the results returned by Google, and users were more easily stuck in coming up with useful keywords and felt time pressured. Finally, users felt it was less physically demanding when they used PopNet (3.00) compared to Google (3.20), but the difference was not significant (\(t = 0.31, p = .382\), as in both cases they needed to browse, search and write ideas on the notepad.

5.2.2 Creativity Support Index of PopNet and Google. Creativity support index (CSI) is a quantifiable measure to evaluate a creativity support tool’s ability to engage users with creative work. CSI includes six dimensions: exploration, expressiveness, immersion, enjoyment, results worth effort, and collaboration [10]. We removed the collaboration dimension in the questionnaire, as our task should be completed independently and did not involve any form of collaboration. We hypothesize that users find PopNet engages them more to do the task in terms of the CSI dimensions, compared to Google. Statistics of CSI are listed in Table 2, where the index for each of the 5 dimensions is in the range of 0-20. Generally, PopNet gets a higher average index from users in all the five dimensions compared to the baseline of Google. Users enjoyed using PopNet (13.60) more to do the visual design task than Google (12.70) but without significant difference (\(t = -0.764, p = .232\)). This is likely because Google is a popular searching tool that many people are already familiar with and use on a regular basis. For the exploration dimension, PopNet (15.40) outperformed Google (11.20)
with significant difference ($t = -2.585, p = .015$). Users found it easier to explore and track different ideas and possibilities with the help of PopNet. As P1 explained during the interview, “By having tons of related visual or text cues, PopNet helped me get out of stuck with thinking of accurate keywords, and it was easy to track the idea following the association links”. Due to similar reasons, users found PopNet (13.60) allowed them to be more expressive and creative compared to Google (11.10) with a significant difference ($t = -1.872, p = .047$). In terms of immersion dimension, PopNet (10.00) has a slightly higher score than Google (9.70) but without significant difference ($t = -0.228, p = .412$). Some users found PopNet less immersive to use as it was a new system they never got touch with before, and it was harder for them to use PopNet without thinking compared to Google. Finally, it was reported that users were significantly more satisfied ($t = -2.389, p = .020$) with the results they got out of PopNet (15.50) than of Google (12.70), matching with the result of performance dimension in NASA-TLX.

5.2.3 User Experience of PopNet Interface. In the questionnaire, we collected users’ opinions about their experience with three main features of PopNet Interface: overview page, association page and search bar. All users claimed that they at least occasionally used these three features. Most of them used overview page and association page more often than search bar. As for the reasons of using the overview page, half of the participants (P3, P4, P5, P7 and P10) mentioned that it was helpful to browse the overview page because of its clear classification and informative content of importance to the pop culture domain. Based on our observation, participants often used overview page as the “starting point” of each of their ideas, which supported their divergent thinking of relating a pop culture domain to many specific things. After picking a thing of their interest, users usually turned to the association page to find links around it.” (It was) really helpful to see ranked pairing things on the association page, as otherwise I would be lost in thinking of connections that fit into the scene myself”, as P5 said during the interview.

While the overview page supported divergent thinking, the association page helped more with convergent thinking of landing on meaningful associative thing(s) to compose the target scene. Among the association types PopNet provided (+People, +Organizations, +Locations, +Objects, +Actions), people (3; P4, P9 and P10), objects (3; P2, P8 and P9) and actions (3; P1, P3 and P5) are most preferred by users, as users can quickly recall plots and enriched the ideation in their mind by browsing these types. Locations (2; P2 and P3) and organizations (1; P6) were also mentioned by several users as their mostly used association types, since iconic locations or organizations were good cues to set on a specific scene. Finally, though not used as much compared to overview and association pages, users pointed out that search bar was useful because 1) when they already have some specific thing in their mind and would like to check more details, search bar provided them with a short cut to the entity/action page, saving them lots of time; 2) when they were stuck with only browsing, they can try some non-domain-specific keywords and utilize the semantic search to associate with scenes in the pop culture domain (e.g., car=>drive, wash=>laundry). Due to the limitation of our data source, sometimes the search function did not return meaningful matching results for users’ free input of keywords. We leave this for future work.

6 DISCUSSION AND LIMITATIONS

6.1 Supporting Other Pop Culture Domains

During the development of PopNet, we focused only on movies and television series. However, pop culture encompasses many more things - music, toys, politics, sports, technology, etc. Our method of constructing the knowledge association network currently relies on plot summaries, which only exist for scripted entertainment. A potential way of extending this approach to other forms of pop culture is to find a place where these things are discussed and try to use the same
technique. Newspapers cover politics, sports, music, and other consumer goods and thus starting with news articles could a promising approach. Another avenue would be to look at online discussions like Reddit threads. A complication with social media is that discussions do not always stay on topic, and it does not have a consistent level of detail that plot summaries do. Journalism is is more consistent, but there is not nearly as much of it.

In addition to extracting knowledge and associations about pop culture, it might also be useful to extract similar information on the brands and messages people want to convey in PopRef images. Although our users had little difficulty understanding brands like Oreo and BMW they could have overlooked potential connections. Some structured information about brands (taglines, products, etc) do exist in Google Knowledge Graph, but that omits lots of associations people have with the products. For example, that kids like to twist Oreos open, or that BMW drivers don’t know how to use their blinkers. Automatically extracting associations for brands, products, and other entities is an open challenge that could greatly enhance creative connections for PopRefs and beyond.

6.2 Supporting Connections in Creative Tasks

As discussed in the Related Work, many creative tasks rely on connections. Much research has focused on supporting divergent thinking like brainstorming, but more effort is needed to focus on support convergent thinking to put together the pieces that get brainstormed.

The combination of structured information and associations is a powerful enhancement to our own cognitive abilities, and knowledge association networks are one way to capture that. In PopNet, we created a stand-alone interface for a one-off task. However, what would be much more powerful is to integrate the knowledge association network into environments where people are already doing work. For example, it could be useful to embed PopNet as a sidebar in Google Presentations to help people add pop references to their slides. More generally, it would be useful to help people integrate knowledge association graphs into their email inboxes. When composing emails, they can piece together bits of information from previous emails they have written that include structured information like peoples names and email, or unstructured associative information such as boilerplate text you copy to all students who want their grade raised. Sentence-level autocomplete [9] is a step towards this, but by reusing one’s existing emails we could enable more useful and personal suggestions.

6.3 Improving PopNet

This system has several limitations that we plan to work on in the future.

First, as an initial step to build pop culture domain-specific network, we choose wiki plot sections as our data source, which is generalizable and informative, but also has limitations. For example, wiki plots missed famous quotes such as “May the Force be with you” from Star Wars and “Joey never shares food” from Friends, as well as iconic objects that never shows in a specific plot, like yellow scrolling text from Star Wars and door frame from Friends. As the next step, we will consider integrating other data sources, like social media discussion into the system as the supplementation.

Second, we only extracted subject-verb-object relations by finding ARG0-V-ARG1 tagging from open information extraction. We thus missed part of relations for entities if they belong to other kinds of arguments. In the future work, dependency parsing could be done to simplify the sentences further and capture more of the relations.

Third, we utilized several AI models to do the automated processing, which have high performance but also bring errors. For example, open information extraction model will recognize “Eddie”, which is definitely a character’s name, as the predicate. This may bring some surprisingly meaningless results to PopNet system. We shall find approaches to reducing these mistakes, such as adding another step to filter out non-verbs from the extracted predicates.
Fourth, as several participants suggested during the interview, we could improve image qualities of entries, especially for actions. We will consider using short cut videos to replace images for actions, so that users could recall the scene more vividly. We can also support searching adjective plus entity in the system, such as “Fat Monica”, by adding more source data for semantic search.

Lastly, we have only tested the automatic construction on 5 pop culture domains: Star Wars, Harry Potter, Game of Thrones, Friends, and Breaking Bad. More thorough testing of other movies and TV shows is required to know how general the pipeline is.

7 CONCLUSION

This paper presents PopNet, a pop culture knowledge association network to support creative connections. We used state-of-the-art NLP techniques to automatically build the network from plain text. We also built an interface that allowed users to interact with the network and support their divergent and convergent thinking. A 10-participant user study showed that, compared to Google, users had better performance and felt more engaged in the creative connection allowed users to interact with the network and support their divergent and convergent thinking. A 10-participant user study showed that, compared to Google, users had better performance and felt more engaged in the creative connection tasks. We also provide insights into supporting connection findings in other kinds of creative tasks.

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