

Community Needs and Assets: A Computational Analysis of Community Conversations

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Abstract

A community needs assessment is a tool used by non-profits and government agencies to quantify the strengths and issues of a community, allowing them to allocate their resources better. Such approaches are transitioning towards leveraging social media conversations to analyze the needs of communities and the assets already present within them. However, manual analysis of exponentially increasing social media conversations is challenging. There is a gap in the present literature in computationally analyzing how community members discuss the strengths and needs of the community. To address this gap, we introduce the task of identifying, extracting, and categorizing community needs and assets from conversational data using sophisticated natural language processing methods. To facilitate this task, we introduce the first dataset about community needs and assets consisting of 3,511 conversations from Reddit, annotated using crowdsourced workers. Using this dataset, we evaluate an utterance-level classification model compared to sentiment classification and a popular large language model (in a zero-shot setting), where we find that our model outperforms both baselines at an F1 score of 94% compared to 49% and 61% respectively. Furthermore, we observe through our study that conversations about needs have negative sentiments and emotions, while conversations about assets focus on location and entities.

Introduction

Understanding the needs and assets of neighborhoods is an important task for non-profits, government agencies, and local leaders to affect positive development within their communities. Such development work can be in the form of shelter programs to alleviate homelessness or educational programs for young adults. However, with limited resources at their disposal, organizations have to choose what to prioritize; whether to focus on resolving the unmet needs or whether to foster the assets of the community they are serving.

In the non-profit literature, a “need” is a discrepancy between “what is” and “what should be”, while an “asset” (resource) is anything that can be used to improve the quality of community life (McKnight and Kretzmann 1993). A “community needs assessment” is a systematic set of procedures that are used to determine needs and assets, exam-

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Post:

My amazing grandmother lives in Flatbush, Brooklyn, and in desperate need of someone to come help her, a therapist and a cool, artsy, and kind community to be around and hang out with. She is struggling with serious anxiety attacks and keeps ending up at the psych ward....I’m looking for any advice on care for the elderly and mental health in Brooklyn, and/or any charities or communities in the area who might be able to help. if anyone has had any experience with this, I would be so appreciative.

Comment:

Flatbush seriously lacking a senior center that is desperately needed!!! Contact Crystal Hudson’s office, she is Chair of Aging Committee for City Council, dedicated to helping with Seniors <https://council.nyc.gov/district-35/>

Label: Need - Support for Special Population

Figure 1: An example of a conversation about community needs; the need in this example is being “Support for Special Population”.

ine their nature and causes, and set priorities for future actions (Witkin and Altschuld 1995). Understanding community needs and assets is a vital domain consideration to help non-profits and government agencies perform their activities better.

Community needs assessments are traditionally done through surveys (Billings and Cowley 1995), focused group discussions (Williams et al. 2020), and manual data analysis by human actors. Manual data analysis includes the synthesis of public open datasets (Al-Qdah and Lacroix 2017) and historical assessment data (Billings and Cowley 1995).

The exponential growth of community-related discourses in social media has led to non-profits only recently incorporating social network analysis (Alonzo et al. 2023) as a part of their community assessments; using tools such as Crowd-Tangle¹ to supplement their traditional methods and study topics of interest in their target communities (White et al. 2023). Analyzing community conversations provides an ad-

¹<https://www.crowdtangle.com/>

A churches charitable work should absolutely be tax deductible. They absolutely do good work. Everything else however should not. Throwing events for members should be taxed money, so should real estate etc etc. You shouldn't be allowed to donate property to a church then it "hires" you and compensates you in letting you live there so you don't pay taxes. There's a million and one tax loopholes involving churches that people exploit.

Label: Asset - Institutional and Civic Asset

Figure 2: An example of a conversation about community assets; the asset in this example is "Institutional and Civic Asset".

ditional valuable lens to established survey-based methods to study a community (Iqbal et al. 2023; Lasri et al. 2023) and increases the validity of findings of such assessments as highlighted by Zohrabi (2013). Another key benefit from traditional methods of needs assessment is that we are not surveying the community and asking them questions, they have free and open discussions from which we are extracting value.

For example, in Figure 1, a community resident is looking for support for senior citizens while another resident comments about how the area has a significant lack of such support. Similarly, Figure 2 includes a comment about the charitable work done by churches in the neighborhood highlighting a key asset in the community. Identifying and locating these community conversations from noisy data will provide strong support to established traditional methods of community assessments. However, due to the large amount of data, manually performing this task may overwhelm human actors (Shah, Cappella, and Neuman 2015). Our task is to identify and extract such conversations leveraging established state-of-the-art methods in natural language processing.

Particularly with the widespread adoption of large language models in social science (Ziems et al. 2023), we need to investigate what differentiates the conversations about needs and assets from other conversations. Such techniques have been used to identify community health needs during the COVID-19 pandemic (S.V. and Ittamalla 2021; Mejova and Manikonda 2023), utilizing NLP techniques. However, the scope of such studies and methods focused on a subset of only needs (health and diet) and does not include linguistic analysis. There is a need for a systematic computational approach to understanding and analyzing community needs and assets (CNA) with a robust dataset for evaluating future methods.

In this paper, we ask two research questions:

- **(RQ1)** Can we computationally extract community needs and asset information from community conversations in social media?
- **(RQ2)** What are the linguistic features that differentiate community needs and assets conversations?

To study our research questions, we model identifying

needs and assets as an utterance-level classification task to deconstruct and find linguistic patterns. An *utterance* is a unit of communication produced by a single speaker to convey a single subject, which may span multiple sentences (Bakhtin 2010; Ziems et al. 2023). Our contributions to this paper are:

1. We introduce a novel Community Needs and Assets (CNA) dataset of conversations from eleven geographical communities on Reddit to identify community needs and assets from natural language conversations. The dataset is annotated by crowd-sourced workers where each conversation is assigned the labels need, asset, or other. It aims to provide a much-needed benchmark for utterance-level classification tasks for mining conversations about community needs and assets in computational social science.
2. Using our dataset, we perform baseline computational analysis using supervised classification, zero-shot approaches, and sentiment analysis to evaluate the feasibility of existing approaches that can be used to extract community needs and assets. We find that zero-shot and sentiment analysis approaches perform poorly off-the-shelf in identifying such conversations indicating that there is a need for such dataset to progress towards a more robust computational analysis of community needs assessments.
3. Using the baseline utterance-level classification model to extract community needs and assets, we take a computational linguistic approach to deconstruct how conversations about community needs and assets are classified by such supervised methods. To our knowledge, our study is the first analysis of needs and assets from a conversational lens that can supplement traditional community needs assessment methods. We find that conversations about need are attached to negative sentiment but not all negative conversations are focused on community needs. Furthermore, asset based conversations are not only attached to positive sentiments but are focused more on identifying specific entities and locations.

Related Work

The widespread use of needs assessment originated in the United States with federal government programming in the 1960s. The concept of urban community assessments and needs assessment was formalized in 1995 (Witkin and Altschuld 1995; Billings and Cowley 1995) as a primary method of discerning the gap between what is available and what should be available i.e. "need" for a target group (in our case an "urban community"). These assessments have become a prominent tool for data collection with the increase in data-driven decision-making for communities and neighborhoods (Kingsley, Coulton, and Pettit 2014; Chowdhury and Sharma 2021). Recent works are transitioning more towards the use of artificial intelligence for such development work (Vinuesa et al. 2020) and integrating social media for assessments (Alonzo et al. 2023). Extant research has utilized social media conversations to deconstruct altruistic requests in Stack Overflow (Althoff, Danescu-Niculescu-

Mizil, and Jurafsky 2014) and linguistic analysis of social comparisons using Twitter (Cui et al. 2022). Our work on identifying the needs and assets of a community from social media conversations can be situated in the same vein as these works. Similar to the linguistic analysis performed by Giorgi et al. (2023) in deconstructing personal narratives, we deconstruct how people identify what is needed and what provides strength to their local community. Furthermore, our work can also be situated alongside recent advances in demographic and geographic inference as well as political analysis of communities on social media (Iqbal et al. 2023; Herdağdelen, Adamic, and State 2023; Lasri et al. 2023)

We utilize an utterance-level classification (Ziems et al. 2023) approach which include classifying dialects (Demszky et al. 2019), emotions (Ortony, Clore, and Collins 2022), hate speech (ElSherief et al. 2021), stance (Dutta et al. 2022), and misinformation detection (Alam et al. 2021). We approach community conversations at the utterance level of abstraction and can be situated alongside the recent advances in stance mining but instead of political ideology (Jiang, Ren, and Ferrara 2023), we focus our work on the identification of community needs and assets, as we provide our CNA dataset to evaluate approaches to computational community needs assessments.

Community Needs and Assets

What are Community Needs?

Existing needs assessment approaches define community needs depending on their target community (Witkin and Altschuld 1995). For a computational analysis, we categorize needs as defined in the “Community Needs Assessment” performed by the New York City Department of Youth and Community Development (DYCD 2022). The categories and sub-categories are as follows:

Basic Needs Describes the fundamental necessities in the neighborhood such as food and nutrition assistance, health care, financial assistance, legal services, transportation, crime prevention, etc.

Education Describes services and programs to help education such as adult education/literacy, college preparation, financial literacy, etc.

Employment Includes services such as career counseling, assistance starting a business, job skills training, etc.

Out of School Time (School) DYCD includes afterschool programs and summer recreation services under this umbrella category - differentiating from education with a focus on recreation.

Family Supports Includes childcare and early childhood development. Additionally, this also covers support for domestic violence victims, family counseling, and parenting support.

Support for Special Population (SP) This category includes services for senior citizens, veterans, or the disabled.

What are Community Assets?

The Community Capitals Framework (Flora, Flora, and Gasteyer 2016) models communities as a system of assets that interact with each other to generate value and capital. Each of these assets is a sub-system of its own (Chowdhury and Sharma 2022) and a taxonomy of the value within the community is already defined by Callaghan (Callaghan and Colton 2008) with four categories of assets:

Human Assets Human assets are the skills and abilities of each individual within a community. Residents who have the ability to build and transform their own community. This includes but is not limited to teachers, community organizers, volunteers, elected officials, and local business owners (Schultz et al. 2000).

Institutional and Civic Assets (IC) Community services like public transportation, early childhood education centers, recycling facilities, and cultural organizations improve the lives of community members, whether they operate as nonprofits, for-profits, or government entities. These institutional and civic assets offer programs, services, and commerce opportunities (Schultz et al. 2000).

Physical or Built Assets It could be a physical location like a school, hospital, church, library, recreation center, or social club, serving as a town landmark or symbol. It may also include unused buildings or vacant land suitable for a community hospice or meeting room on the second floor. Alternatively, it could be a public space like a park, wetland, or open area already owned by the community (Schultz et al. 2000; Callaghan and Colton 2008; Flora, Flora, and Gasteyer 2016).

Cultural Assets Cultural assets are the arts, music, language, traditions, stories, and histories that make up a community’s identity, character, and customs. This asset is harder to define as it may contain aspects of a community such as ethnic, racial, or religious diversity. It may also contain concrete things such as historical sites or festivals and fairs (Callaghan and Colton 2008; Flora, Flora, and Gasteyer 2016; Schultz et al. 2000).

The CNA Dataset

Reddit is a social media platform that has been extensively used for several computational social science studies (Giorgi et al. 2023; Lokala et al. 2022). It is known for its forum and discussion-oriented post structure with an emphasis on separated communities (*subreddits*). This allows conversations to be categorized and targeted to only specific communities and suits our community-based analysis.

Dataset Construction

Keyword and Subreddit Selection We create a dataset by collecting posts and comments from 11 *subreddits* as shown in Table 1. We start with a seed set of keywords relevant to the community needs (1) *community*, (2) *community needs*, (3) *community school*, (4) *programs services household receive*, and (5) *welfare* to ensure initial relevance to community discussions.

Community	Count
Manhattan	4
Bronx	33
Queens	46
Brooklyn	264
NYC	1,449
Rochester	599
Colorado Springs	400
Virginia Beach	200
Jacksonville	200
Mesa, AZ	116
Oklahoma City, OK	200
Total	3,511

Table 1: The dataset statistics by Reddit communities in our CNA dataset.

programs services household receive was selected from the questionnaire used by an actual needs assessment (DYCD 2022) to see if such keywords help with finding relevant conversations. Other keywords were experimented with as well but did not add any new conversations in addition to the ones provided by these five keywords.

We selected 11 subreddits, 5 of them representing each of the communities in the New York City area along with the subreddit of *Rochester* to allow for a needs assessment of mid-sized cities within similar geographic locations. We selected the five boroughs of New York and Rochester because the state of New York provides socioeconomic diversity within a shared regional context. By including examples from different boroughs with diverse demographics we can account for differences in needs and assets. As a global city, the population of New York City represents tremendous cultural, ethnic, and linguistic diversity which adds to the generalization of our dataset.

However, New York City and Rochester combined are still more socially and economically liberal. Focusing only on NYC communities misses potential insights from other urban regions that are more conservative for comparison. Needs and assets conversations may differ across geographic and political contexts. To enable our CNA dataset to be generalizable to urban communities, we further included the five most conservative big cities in the United States in our dataset (Tausanovitch and Warshaw 2014): (1) *Mesa, AZ*, (2) *Oklahoma City, OK*, (3) *Virginia Beach, VA*, (4) *Colorado Springs, CO*, and (5) *Jacksonville, FL*

For these *subreddits*, we retrieved all posts and comments using a widely used library² limiting our search results to posts that have at least 5 comments to ensure there was some minimal amount of user engagement.

Corpus Filtering We further synthesize our community needs corpus from the initial Reddit corpus with a natural language inference (NLI) approach where we calculate the probability of entailment, contradiction, or neutral relevance between each conversation, premise P , and our hypothesis

²<https://praw.readthedocs.io>

According to the given text, which of the following is this comment talking about?

- Need: A community issue, problem, or need (Something negative the community is concerned with. Or something the community is missing)
- Asset: A community highlight, strength, or asset (Something positive the community has)
- Other: Other (If unsure write what it is about)
- None: None of the above (the comment is about something else and has nothing to do with the community)

Figure 3: Prompt for zero-shot text classification of community needs conversation

What kind of programs, services, or needs is this comment talking about?

- Basic Needs
- Education
- Employment & Career Advancement
- Out of School Time
- Family Supports
- Support for Special Population
- Other

Figure 4: Question for community needs

“ H : Community needs are important”. This allows our corpus to only contain conversations that are semantically close to the idea of community needs. We adapted this method to compute semantic similarity from existing approaches for aggregated stance mining in computational social science literature (Dutta et al. 2022; Halterman et al. 2021; Khudabukhsh et al. 2022; Chowdhury et al. 2024). We define $NLI(P, H)$ as a function, where P is the premise and H is the hypothesis, yielding an output *oent, con, neu*. For a conversation c_i in corpus C , we calculate the entailment ratio $ent(c_i, H)$ as the fraction of sentences in c_i that entail the hypothesis H .

The final corpus C_{final} only contains conversations c_i that have an entailment ratio of over 0.5, resulting in the distribution shown in Table 1.

Crowd Sourced Annotation

We annotated each of our comments in C_{final} with crowd-sourced workers through an anonymized Amazon MTurk task³. The primary three questions are given in Figure 3, Figure 4, and Figure 5.

The first question in Figure 3 asks the annotator to identify if the conversation is about need, asset, or irrelevant to

³Task outline: https://osf.io/sydf2/?view_only=b3c0a843e6244f4d99a6b349156adad8

What kind of highlight, strength, or asset is this comment talking about?

- Human Assets
- Institutional and Civic Assets
- Physical Assets
- Cultural Assets

Figure 5: Question for community assets

the community. The second question in Figure 4 determines (if the conversation is about a need) what category of need is it about. The third question in Figure 4 determines (if the conversation is about an asset) what category of asset is it about. Each comment was annotated by three independent annotators. To ensure the reliability of annotations, we limited annotators to be located within the USA (conversations in our corpus are from communities within the USA) and have MTurk Master’s qualification.

Compensation We compensate the annotator 0.15 USD for each instance where each batch with 20 instances would thus fetch 3 USD. Compensation is grounded in prior literature as the initial pilot by the authors estimated \$12/hour compensation with a completion time of 15 minutes per task and \$3/task. This is more than the US minimum wage (\$7.25) and falls within the range reported in extant literature (\$6/hour in Leonardelli et al. (2021); \$7.25/hour in Bugert et al. (2020); and \$13/hour in Bai, Ritter, and Xu (2021)).

Demographic Approximately 50% of our annotators are from small cities and rural towns, while the remaining annotators combined come from larger than mid-sized cities as shown in Figure 7. The majority of our annotators are within the age range of 30 – 39 (60%) as shown in Figure 9 while approximately 45% of our annotators have a Bachelor’s degree (Figure 8).

Inter-Annotator Agreement We measured inter-annotator agreement using the statistic Krippendorff’s α to compare agreement between the annotators. The agreement between our three independent annotators per batch was at 0.45. The moderate Krippendorff’s alpha agreement indicates that identifying need and asset conversations are inherently subjective, even among human annotators. It also highlights the linguistic challenge of consistently distinguishing such abstract ideas and concepts that can be interpreted differently. There may be an element of subjective perspective or individual bias that shapes how people label these conversations as personal experiences influence perceptions (Hube, Fetahu, and Gadiraju 2019).

Furthermore, the moderate Krippendorff’s alpha also suggests inherent noise in using crowdsourced annotations for this dataset where disagreements may lead to inconsistent labels, especially for borderline cases. As can be seen in the example in Figure 6, one comment can have examples of both asset and need leading to confusion among annota-

Need:

This. No one wants to live in a dump but paying \$2500 a month is a pox on anyone’s ability build a solid financial future. I know many homeowners in the midwest that don’t even pay that on their home mortgages. I understand that NYC is far above its darkest days but it’s still grimy, the infrastructure isn’t in great shape and has a very deep income inequality. I think it’s hard to justify living in this city when it’s also one of the most expensive places to rent/own in the country. Asset: But, the culture, food, and career opportunities are second to none. People love this city, they just wish it wasn’t so damn expensive.

Figure 6: An example of a conversation that had three annotators label need, asset, and other respectively. The text in the beginning shows what can be considered need conversation and the second part shows asset conversation. The final label of need was assigned because conversations about need forms the majority of the post. This challenging example contextualizes the low agreement between annotators of the CNA dataset.

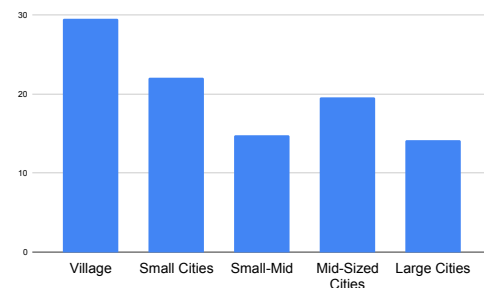


Figure 7: The distribution of community background for the human annotators for CNA dataset. The y axis represents the percentage of annotators.

tors. The final label for each conversation was decided as the majority label from the three annotators. We further annotated the dataset with one graduate student researcher to break three-way ties in the case of three different labels assigned by the three crowdsourced annotators. The researcher is familiar with the annotation guidelines, and the community needs and assets domain, and has research experience in urban data science. Hence, this annotator was a reliable source of quality control over the annotations by the crowdworkers (Hsueh, Melville, and Sindhwani 2009).

Categorizing Needs and Assets Upon studying the overall distribution of categories within need based conversations in Figure 10, we see that the annotators defaulted to the categorizing a need conversation as **Basic Needs** in our dataset, indicating that most of the conversations in our dataset are focused on the fundamental necessities in a neighborhood, while the second most popular discussions are between **Education** and **Employment**. Upon studying

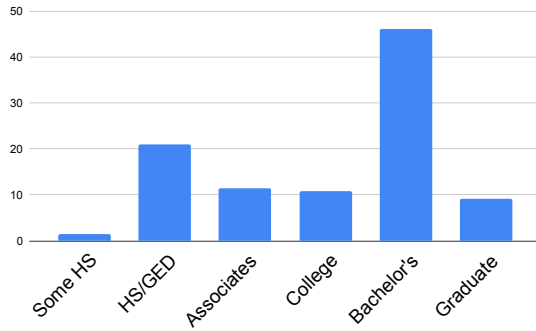


Figure 8: The distribution of educational background for the human annotators for CNA dataset. The y axis represents the percentage of annotators.

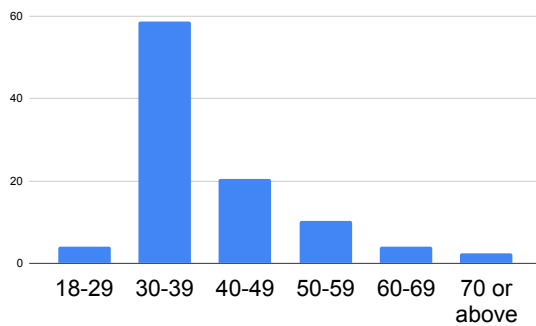


Figure 9: The distribution of age for the human annotators for CNA dataset. The y axis represents the percentage of annotators.

the overall distribution of categories within asset conversations in Figure 5, we see that there is no such default selection for such conversations. There is an even distribution for the type of asset within the community conversations in our dataset.

Classification of Community Needs and Assets

We define the task of identifying community needs and assets as an utterance-level classification task where a model has to predict the target labels need, asset, and other from each natural language conversation $c_i \in C_{final}$ where C_{final} is the corpus of conversations.

Evaluating the classification of community needs and assets is difficult, as can be seen with the moderate inter-annotator agreement we discovered through our annotation process. In order to evaluate the efficacy of our dataset and the separability of needs & assets as an utterance-level classification task, we designed two baseline approaches to evaluate the classification of community needs and assets from conversations along our utterance-level classification approach. In this section, we describe each of our baseline methods along with our supervised approach in detail.

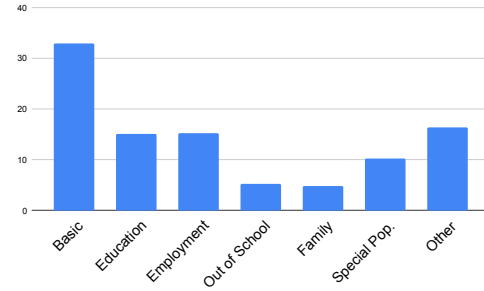


Figure 10: Distribution of categories of needs in conversations in our CNA dataset. The y axis represents the percentage of data categorized as one of the taxonomies.

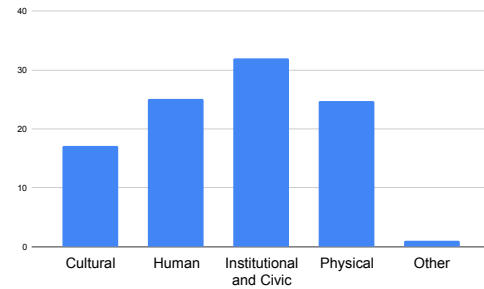


Figure 11: Distribution of categories of assets in conversations in our CNA dataset. The y axis represents the percentage of data categorized as one of the taxonomies.

Sentiment Classification

Sentiment classification is a widely used method for opinion mining in online communities (S.V. and Ittamalla 2021). Particularly, sentiment and opinion mining approaches have been used to study particular communities in domains such as health care (Tavoschi et al. 2020; Chintalapudi et al. 2021). Expanding from these approaches, we can assume that needs-based conversations can be of negative sentiment while asset-based conversations can be of positive sentiment and assign the labels positive to comments labeled as asset, negative to comments labeled as need, and neutral to conversations not related to either. But is that assumption of need to negative and asset to positive robust enough to perform community needs and asset extraction using baseline sentiment classification? We aim to answer this question using our experiment. We use the sentiment classification model derived from a *RoBERTa-base* model trained on approximately 124 million tweets from January 2018 to December 2021 and fine-tuned for sentiment analysis with the TweetEval benchmark (Loureiro et al. 2022; Barbieri et al. 2020). We utilize a model previously trained on Twitter data to ensure that it can handle noisy social media conversations in our Reddit dataset.

Observed	asset	278	26	172
	need	32	552	255
	other	316	992	889
		Positive	Negative	Neutral
		Predicted		

Figure 12: The Confusion Matrix for the Sentiment Classifier. Green indicates True Positive samples, while red is used to highlight negative sentiment in other categories.

LLM Zero-Shot Classification

We further utilized a zero-shot text classification method using a popular and accessible large language model (LLM) - Google’s PaLM2 (Chowdhery et al. 2022). We designed a prompt with the best practices prescribed by Ziems et al. (2023) with a particular focus on mimicking real-life multiple-choice questions. Our prompt as shown in Figure 3 is the exact same as the question we asked our human annotators. Recent studies have shown that LLMs outperform human annotators in labeling tasks (Gilardi, Alizadeh, and Kubli 2023; Huang, Kwak, and An 2023; Wang et al. 2023), and our analysis of community needs and assets wanted to accommodate for such findings as well. In our usage of PaLM2, we tuned the *temperature* parameter for text generation to 0.1 to introduce some non-determinism while also keeping the classification as consistent as possible. We performed a sweep of temperature settings from 0 to 1 at an increment of 0.1 and selected the highest-performing one.

Supervised Classification

We developed a classification model utilizing a pre-trained language model BERT (Devlin et al. 2018), adding a multi-class text classification layer on top that we fine-tuned using our CNA dataset with target labels need, asset, and other. Furthermore, we also trained classifiers for categories within each of the primary labels. We hypothesize that differentiating between need, asset, and other is possible if the data can be classified to a high degree of accuracy while categorizing further into the taxonomy of needs and assets will be difficult. We trained all our classifiers for 5 epochs, with an initial learning rate of $5 * 10^{-5}$ using Adam optimizer (Kingma and Ba 2017), with a training set of 80% and a validation set of 20%. We discuss our results in the following section.

Results and Analysis

RQ1: Classifying Needs and Assets Conversations

Baseline Classification The performance of the three classification models is shown in Table 2. Our supervised classification approach outperforms both sentiment and llm zero-shot classification with a macro F1 score of 0.94, while

method	label	precision	recall	f1-score
Supervised	asset	0.93	0.94	0.94
	need	0.89	0.95	0.92
	other	0.97	0.95	0.96
	macro	0.93	0.95	0.94
	weighted	0.95	0.95	0.95
Sentiment	asset	0.44	0.58	0.50
	need	0.35	0.66	0.46
	other	0.68	0.40	0.51
	macro	0.49	0.55	0.49
	weighted	0.57	0.49	0.49
LLM	asset	0.44	0.84	0.58
	need	0.51	0.67	0.58
	other	0.82	0.57	0.67
	macro	0.59	0.69	0.61
	weighted	0.69	0.63	0.64

Table 2: Results of all the classification model evaluations on the validation set of the CNA dataset. All the results are the mean of 10 runs over the validation set to account for randomness.

the other two baseline methods struggle at F1 scores of 0.49 and 0.61 respectively.

Sentiment Analysis Our baseline sentiment classification approach in Figure 12 shows that 65% of need conversations are classified as negative, which indicates that need conversations have negative sentiment attached to them. Similarly, 58% of asset-based conversations have a positive sentiment. To further test the validity of this claim, we perform a chi-squared test of association between (1) need conversations and negative sentiment, and (2) asset conversation and positive sentiment. The null hypothesis is that there is no association between the two variables while the alternate hypothesis is that there is. We have included the contingency tables for the tests in the appendix. In both cases, the *p-value* is less than 0.01 indicating that we can reject the null hypothesis of no association between the two variables.

Our classification and hypothesis testing together indicate that while need conversations may have negative sentiment, not all negative sentiment conversations are focused on need. Similarly, asset conversations may be statistically inclined towards positive sentiment but not all positive conversations are discussions about community asset. This simple but important distinction clarifies why in the study of community needs and assets, we need a robust classifier instead of baseline sentiment classification. This indicates the difficulty in recognizing assets (compared to needs) and why human annotations are a necessity to build models to identify such conversations about a community.

Categorizing Needs and Assets To further deep dive into our labeled need and asset conversations, we analyzed the performance of our classifier after training it on the further categories of each type of conversation. The results are given in Table 3. Our need category classifiers are capable of detecting Employment and Education labels decently well but it performs best for Basic Needs on our validation set. Sim-

class	label	precision	recall	f1-score
need	Basic Needs	0.82	0.92	0.87
	Education	0.67	0.63	0.65
	Employment	0.8	0.73	0.76
	School	0	0	0
	Family	0	0	0
	SP	0.57	0.8	0.67
	Other	0.66	0.75	0.7
	asset	Cultural	0.86	0.5
	Human	0.67	0.92	0.78
	IC	0.84	0.84	0.84
	Physical	0.70	0.56	0.62
	Other	0.0	0.0	0.0

Table 3: Results for classifying need and asset categories on the validation set of our CNA dataset. All the results are the mean of 10 runs over the validation set to account for randomness. SP stands for “Support for Special Population”, IC stands for “Institutional and Civic”, and School stands for “Out of School Time”. F1-score of 0 in this table indicates that our model failed to classify the instances.

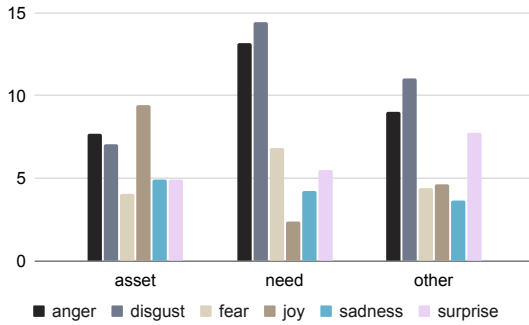


Figure 13: The distribution of emotions for need, asset, and other classes in the dataset. The y axis displays the percentage of labels that were assigned the emotions. *neutral* emotion was removed as that is the majority at over 50% for all 3 classes to allow for a cleaner picture.

ilarly, our asset category classifier performs best for Institutional and Civic assets. This phenomenon can be explained due to an existing pattern of identifying entities when talking about assets and highlights in a community.

RQ2: Distinguishing between Needs and Assets Conversations

Emotion Analysis We dive further into the sentiment analysis of need and asset focused conversations by analyzing the emotions of the conversations of each of our labels. We utilize a text classification model fine-tuned on multiple emotion classification datasets (Hartmann 2022) to classify each of the conversations in our corpus into one of the 6 emotions (and one neutral class). The results shown in Figure 13 indicate the distribution of the emotions among our three classes without the neutral class. Neutral is the pre-

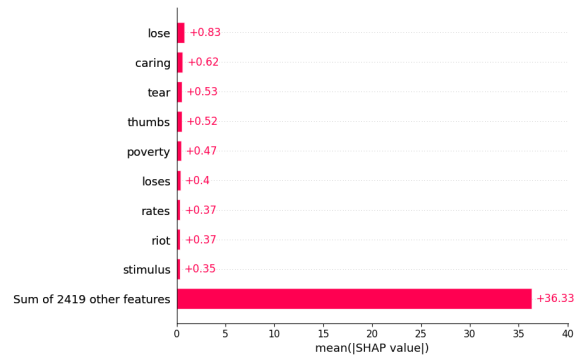


Figure 14: Top 10 word combinations that contribute to the classification of a conversation as need

dominant emotion in all our conversations (60%), indicating that emotion does not play a strong role in the linguistic differences among need and asset conversations. Removing the neutral class from the Figure 13, it is important to note that need conversations have a stronger leaning towards the emotion of anger and distrust and the least amount of joy compared to other labels, while asset conversations have a higher percentage of the emotion joy but an equal amount of anger and disgust. We have included the figure with the neutral class in our appendix.

Deconstructing Needs and Assets We utilized the SHapley Additive exPlanations (SHAP) by Lundberg and Lee (2017) which uses a game-theory inspired method that attempts to enhance the interpretability of machine learning models by computing the importance values for each feature of individual predictions - in our case, the features are words that contribute the most to the classification of each of the labels.

Figure 14 displays the top 20 words that contribute the most to the classification of 200 samples of conversations classified as need. The words with negative connotations such as *poverty*, *lose*, *tear*, appear to have the strongest contributions to the need label.

In contrast, as shown in Figure 15 conversations classified as asset have a significant focus on words such as *places* and *donations*, words that can relate to identifying a specific entity. This also follows the results we discovered with categorizing asset in Table 3 where we hypothesized that conversations related to Institutional and Civic assets are easier to identify due to the focus on concrete entities.

We calculate the number of entities in each conversation in the dataset using named entity recognition, particularly limiting entities to type: (1) ORG, (2) NORP, (3) GPE, (4) PERSON, (5) WORK_OF_ART. Using the number of entities we perform a one-way ANOVA test to compare the mean number of entities of asset conversations relative to all other conversations. Here, the null hypothesis is that the mean number of entities for asset conversations is equal to the mean number of entities in all other conversations. The alternate hypothesis is that the mean number of entities is greater for asset conversations. At a standard significance level of

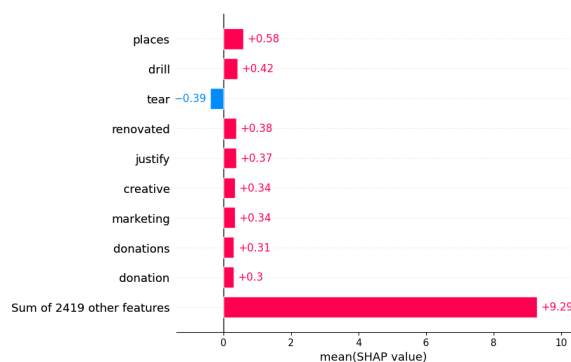


Figure 15: Top 10 word combinations that contribute to the classification of a conversation as asset

5%, we get the p -value at 0.006 and as a result, we can reject the null hypothesis. This indicates that asset conversations may be more location and entity-focused, highlighting the strengths of the community compared to other conversations.

Performance In The Wild

To verify the practicality and robustness of training a classifier using our CNA dataset, we applied our supervised classifier to 23,938 random Reddit conversations from random communities. From these conversations, 1,565 were classified as asset conversations and 1,525 were classified as need conversations. We randomly picked 50 asset, 50 need, and 100 other conversations to manually verify the accuracy of our classifier. We measured a macro precision of 0.89, recall of 0.91, and f1-score of 0.90 for in-the-wild performance. The high precision and recall of our classifier demonstrates promising generalization to unseen data indicating that most classified instances in the annotated sample were true positives.

Conclusion

A computational approach to identifying community needs from conversations is an important domain consideration for local non-profits and government agencies to better allocate their resources to foster the development of their communities. At present, manual approaches are used but with exponentially increasing amounts of data - samples of surveys do not always capture the full picture. To help decrease this manual burden, we take a computational approach to extracting community needs and assets (CNA) and provide a dataset of 3,511 related conversations from Reddit with human-annotated labels for need, asset, and other. Furthermore, we introduce a baseline community needs and assets (CNA) classification approach and compare it to the zero-shot capabilities of large language models along with sentiment analysis to evaluate the usefulness of our CNA dataset. Throughout the paper, we answer two research questions:

RQ1: Can we computationally extract community conversations focused on needs and assets? Present state-of-the-art sentiment analysis and large language models strug-

gle to differentiate community conversations about need, asset, and other. Classifying and extracting such conversations requires a dataset to fine-tune such machine learning models. Through the use of a supervised approach, we show that it is possible to identify these conversations, and also show that further breakdown and categorization of need and asset require greater samples of these low-resource conversations.

RQ2: What are the linguistic features that differentiate community needs and assets conversations? Our sentiment and emotion analysis on conversations indicated that in our dataset, overall need conversations have a slight skew towards negative sentiment along with emotions of *disgust* and *anger*. Similarly, asset conversations have the opposite skew towards positive sentiment and include emotions of *joy*. Furthermore, word contributions and hypothesis testing on number of entities in conversations also indicate that asset-based conversations are focused on locations and places indicating that conversations are highlighting a specific entity that can be classified as an asset.

Future Work We plan on expanding our dataset further to incorporate multi-platforms (not just Reddit), and a greater number of conversations such that we can dive even deeper into the categorization of conversations regarding needs and assets. Furthermore, we use a simple classification approach; a further study on deep neural networks and their explainability, leveraging the state-of-the-art chain of thought method on zero-shot classification explainability on large language models for example would provide a deeper understanding of the community needs and assets conversation phenomena. This will increase the robustness of our method and lead the way into an AI-driven approach to community needs assessment that we hope to pilot in the field for exciting results. The future scope of this work can expand not only into real-world applications for non-profits and government agencies, but can also drive theoretical and linguistic understanding of people's wants and needs.

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Paper Checklist

1. For most authors...

- (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? **Yes**
- (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? **Yes**
- (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? **Yes**
- (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? **Yes**
- (e) Did you describe the limitations of your work? **Yes**
- (f) Did you discuss any potential negative societal impacts of your work? **Yes**
- (g) Did you discuss any potential misuse of your work? **Yes**
- (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? **Yes**
- (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? **Yes**

2. Additionally, if you ran machine learning experiments...

- (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **Yes, and code has been included as part of the supplemental material.**
- (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **Yes**
- (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? **Yes**
- (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **Yes, and it has been added in the Limitations section**

- (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? **Yes**
- (f) Do you discuss what is “the cost“ of misclassification and fault (in)tolerance? **Yes**

3. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity...**

- (a) If your work uses existing assets, did you cite the creators? **Yes**
- (b) Did you mention the license of the assets? **No, because the license of the assets are mentioned within the cited paper**
- (c) Did you include any new assets in the supplemental material or as a URL? **Yes**
- (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? **Yes**
- (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **Yes**
- (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see ?)? **Yes**
- (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see ?)? **No, because it is a relatively simple dataset. But when we release it publicly such methods will be followed.**

4. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity...**

- (a) Did you include the full text of instructions given to participants and screenshots? **Yes, and it has been included in the appendix**
- (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? **Yes**
- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? **Yes**
- (d) Did you discuss how data is stored, shared, and de-identified? **No, because we mentioned that it will be shared once the paper is accepted.**

Appendix

Limitations and Ethical Concerns

Limitations Our neural models were trained on one NVIDIA P4 GPU with 8GB RAM, where the maximum training time was 10 minutes for 2,418 conversations for 5 epochs. Local non-profits (with scarce funding) may not have access to such GPUs. A more optimized training and inference approach will be required to implement this for such use cases.

We assumed that community needs can be classified into categories given by assessments done in the past. However, these categories are by no means exhaustive. But linguistically, further work is required into how people approach a conversation regarding needs and we need to deconstruct such an approach computationally to provide a more robust solution. Since our corpus in Reddit is already in the form of discussions such deconstruction was not necessary - but our future work will aim to broaden the modalities of conversations to other aspects such as focused-group discussions, one-on-one conversations, town hall meetings, etc. We deconstruct each category of these conversations through multiple methods. However, our approach is not an exhaustive list of all possible ways such analysis can be done.

The Reddit communities represent a narrow demographic that does not capture the full diversity of opinions and people present in their respective communities. Reddit users tend to be younger and more technologically inclined, and hence not fully representative of the population. The voices captured are limited to those actively engaged in these online spaces which may result in the needs and perspectives of marginalized communities being underrepresented. Furthermore, conversations are shaped by what issues and strengths users are willing and able to discuss online, which may introduce bias and under-representation of sensitive topics compared to a random sampling of the population.

Ethical Concerns All methods in this paper are evaluated on our CNA dataset, but we believe that the linguistic understanding of needs and assets can be applied to similar cases. Furthermore, our dataset was built using only publicly available conversations that any user can view (without requiring to log in to Reddit) and was collected using their public-facing API. The dataset will be released publicly upon the acceptance and publication of this paper and according to the Findable, Accessible, Interoperable, and Reusable (FAIR) principles. However, there are several ethical concerns when working with such public social media data. It is important to note that the users did not consent to any research studies, and this is an issue similar to a larger issue of using publicly available social media data in research (Giorgi et al. 2023).

Privacy Concerns In addressing specific concerns related to the ethical considerations in working with public social media data, it is crucial to acknowledge the unique characteristics of Reddit posts and comments. Reddit inherently maintains a level of user anonymity, where individuals can engage in discussions without revealing their real identities. Furthermore, the entities and locations mentioned in

sentiment	negative	other
ground truth		
need	552	287
other	1018	1655
sentiment	positive	other
ground truth		
asset	278	198
other	348	2688

Table 4: The contingency table for two chi-squared tests of association: (1) need and negative sentiment (top table), and (2) asset and positive sentiment (bottom table)

the posts are treated as public information, as they pertain to community-related discussions. The individuals referred to in the comments are public figures, such as community service providers or local politicians, who actively contribute to the community or public sphere.

To ensure privacy and adhere to ethical standards, we implemented a rigorous process during the dataset creation. A dedicated graduate student researcher meticulously reviewed the entire CNA dataset. The primary objective of this review was to confirm that no personal information leakage occurred and that the dataset exclusively contained the names of community-related individuals. This thorough examination aimed to mitigate any potential risks associated with privacy concerns and reinforce our commitment to handling public social media data responsibly. We recognize the importance of maintaining the integrity of the data and are dedicated to transparently documenting and addressing these ethical considerations in our research. The final dataset will be made publicly available upon the publication of the paper.

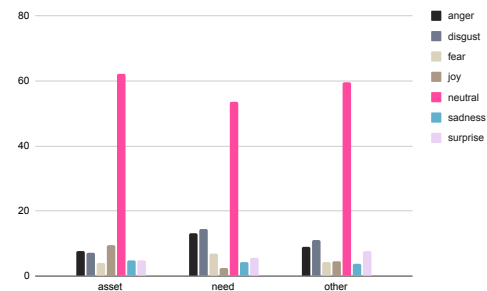


Figure 16: The distribution of emotions for need, asset, and other classes in the dataset. The y axis displays the percentage of labels that were assigned the emotions. This includes the *neutral* emotion that was removed from Figure 13 for a cleaner picture.