Outline

- Our Proposal: **Social Network Analysis**
- Proof of concept
- Segmentation
- Markov chain
- How many people to solicit
- Bonus Analysis
- Conclusion

Our proposal and Proof of Concept

Status quo

Process owners feel that the scoring model is **short-term oriented**

The charity manager demands a **solicitation technique** to build long-term relationship with donors :

- The new segmentation strategy should determine who should be solicited and how often
- The new scoring model should be able to support new budget constraints

From an operational model to a value based model

Current scoring model shortcomings: The previous segmentation model was based on quantitative variables such as recency, frequency, average amount etc.

These variables must not occult the importance of values and preferences as a driver of donations, some campaigns may focus on some themes i.e. poverty, malnourishment which may particularly resonate with some donors.

This presentation assumes that each of the yearly campaigns is characterized by a distinct set of values.

Our Proposal: Social network analysis

Donors come in **all shapes and sizes**

- But the relationship between the charity and donors is most simply characterized by
  - the campaigns for which a donor was solicited
  - the campaign for which a donor actually donated

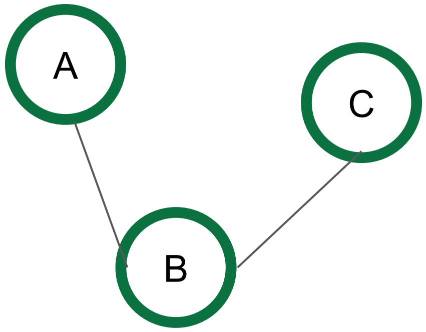
Donor behavior is not fixed in stone, some donors can be **incentivized to donate**, some donors can be **forfeited** because they are **not solicited at the right time**

- We offer a new scoring model based on social network analysis
  - Donors are segmented based on the campaigns they donated to
  - Donors are segmented based on how similar they are to other donors
  - Segments are characterized by metrics from the initial scoring model, included but not limited to: profitability metrics and demographics
- Among donor segments are a common set of connections which we will refer to as network

What “connects” donors?

We performed a **social network analysis**. Two people are connected if they have donated to the same campaign. Under the assumption that each of the yearly campaigns has a distinct message, we can infer that two people that are connected in the network share **some of these same values or habits**.

Different communities of donors are therefore delineated. This gives a more **fine-grained** definition of similarities between users upon which we can construct a solicitation strategy



Example: Donors A and B both have at least one campaign in common. Donors B and C also have up to one campaign in common.

Our method (explanation)

We started by retrieving all the people that **donated to a campaign in 2019**. Only for them can we know which values they adhere to.

We then take a sample of these people (n=150) to make sure the computations do not become too heavy and visualisations can be made. This constraint would not be as stringent when the method is put into production.

We **follow these 150 people until 2023**. We compute a transition matrix from segment to segment and finally decide how many people should be solicited per campaign.

Disclaimer

Due to the complexity of social network analysis, the following analysis is a **small-scale proof of concept** that relies on a sample of **150 users**:

- We ensured that this sample was representative of status, gender, donor behavior
- Our sample draws 150 users who have donated to at least one of the six campaigns in 2019
- Our main aim is to provide a method that scales easily

Segmentation

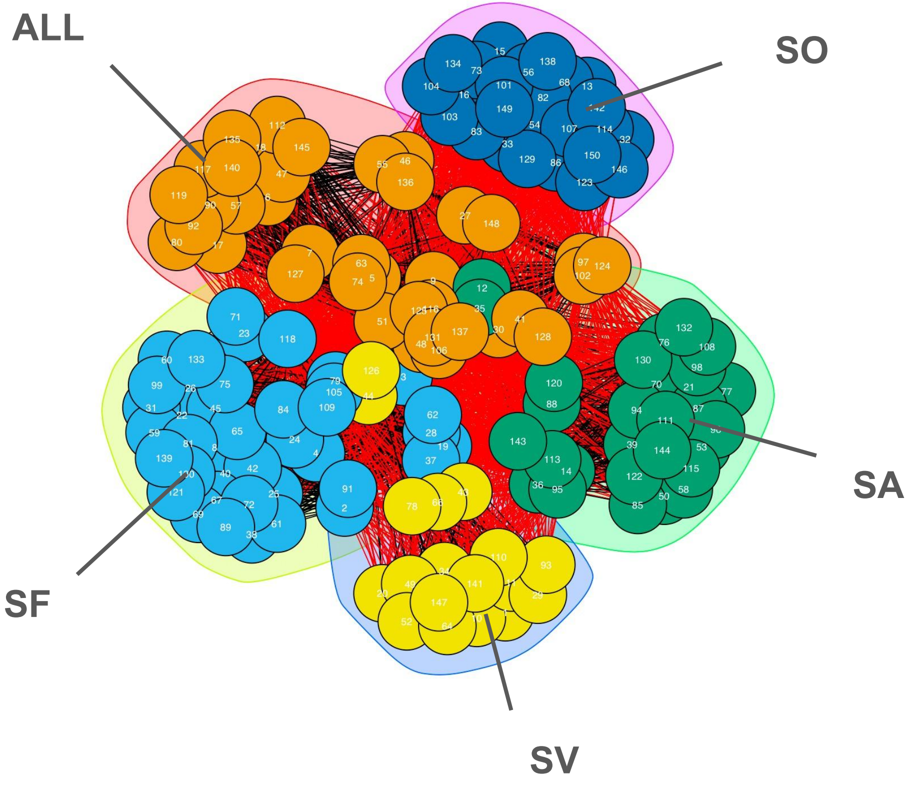
Our new segmentation

TREND SETTERS	ALL	• Average profit after variable cost: 91€ • Total donation yearly: 96€ • 25% of sample	• Really cares about SJ and SO, but can donate to all campaigns • They are the most flexible in terms of campaigns and values
SA FOCUSED	SA	• Average profit after VC: 84€ • Total donation yearly: 89€ • 19% of sample	• Really cares about SA, will sometimes donate to SV, SF • Has some influence on the network
LONERS	SO	• Average profit after VC: 76€ • Total donation yearly: 81€ • 17% of sample	• Only cares about SO • Lowest influence over the network
STRONG HEADS	SV	• Average profit after VC: 76€ • Total donation yearly: 81€ • 12% of sample	• Really cares about SV, will sometimes donate to LAL or SJ • Dissimilarity with other users
SF FOCUSED	SF	• Average profit after VC: 69€ • Total donation yearly: 73€ • 27% of sample	• Cares about SF, will sometimes donate to other campaigns • Has some influence over the network

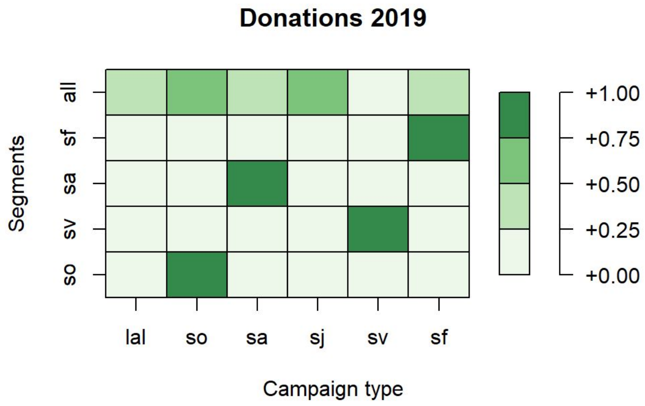
Visualizing donor segments - 2019

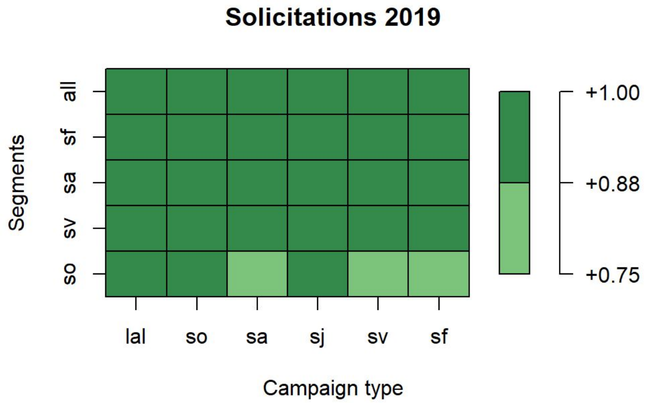
Segments interact with each other:

- If two donors have a line between them, that means they **both donated to the same campaign and share certain values/habits**
- If a segment is more “central”, we can conjecture that this segment is **more flexible than others in their values/behaviour**



Past solicitation and new segments - 2019



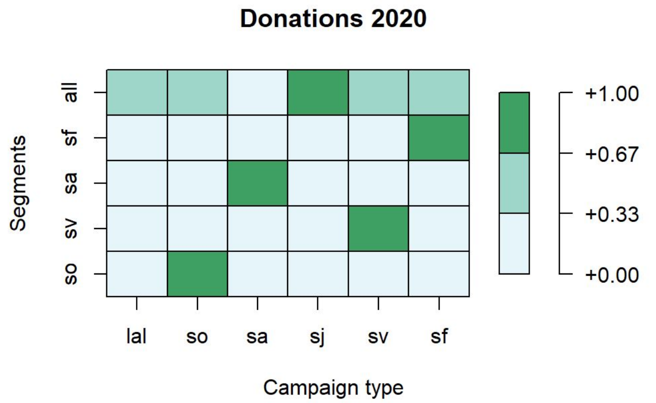


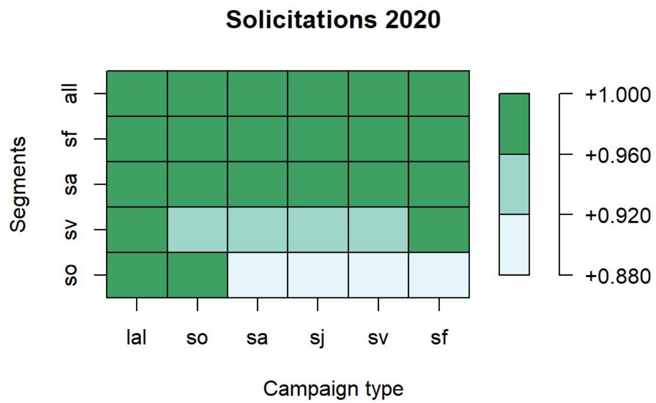
Looking at past solicitation behaviour in view of the newly defined segments proves to be insightful

A very **uniform and highly frequent** targeting from the charity is contrapposed to **stark and punctual** donations by the donors

An issue is raised regarding the efficiency of the targetization routine. Values/timings could become a **sensible signal for the timings of solicitations**

Past solicitation and new segments - 2020





Performing an equivalent study in 2020 gives support to the **stability** of this analysis

The **same behaviour** can be delineated for both the different segments and the charity, even though such stability is evidenced only in a 2-year period

This confirms that the proposed network-based segments could be **traced down across different years**

Markov Chain

Transition matrix Year on Year (computed from 2020-2021)

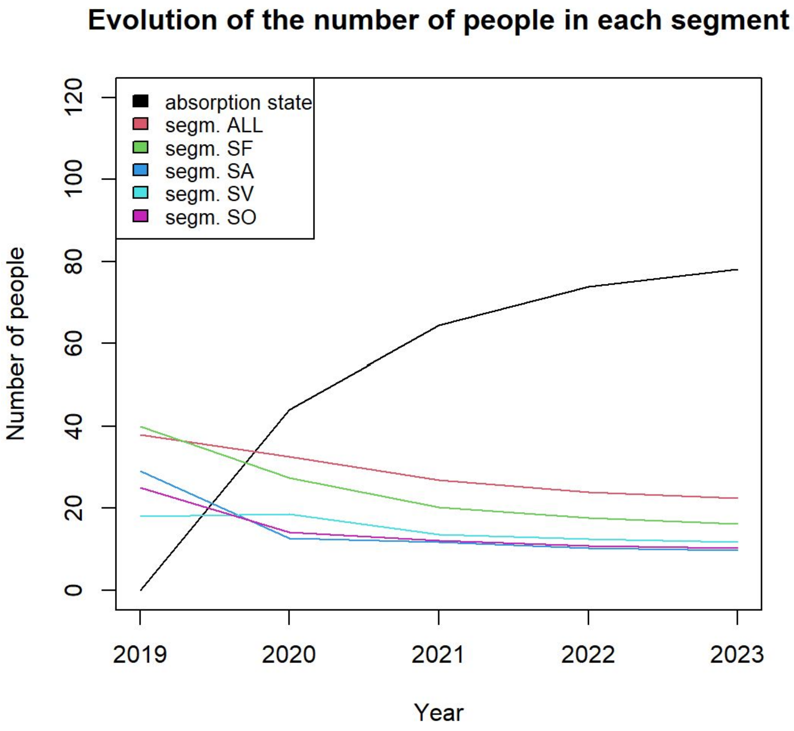
We proceeded by computing the probability of changing segments during the years 2020-2021. We defined **segment 0** as grouping those that did not donate to any 2021 campaign. Empirical evidence suggests that our absorption state as defined above is **not final**, as shown by the transition matrix below which we will use from here onwards:

	Ø	**ALL**	**SF**	**SA**	**SV**	**SO**
Ø →	0.76	0.08	0.04	0.04	0.04	0.04
ALL →	0.28	0.28	0.16	0.06	0.09	0.12
SF →	0.36	0.25	0.18	0.11	0.04	0.07
SA →	0.14	0.21	0.29	0.07	0.14	0.07
SV →	0.22	0.17	0.17	0.22	0.11	0.11
SO →	0.44	0.11	0.11	0.00	0.22	0.11

Evolution of segment size

Empirically, we expect around half of the people that donated in 2019 to not donate to any campaign in 2023, the remaining proportions between segments is as follows:

Trend Setters	15%
SF Focused	10%
SA Focused	7%
Strong heads	8%
Loners	7%

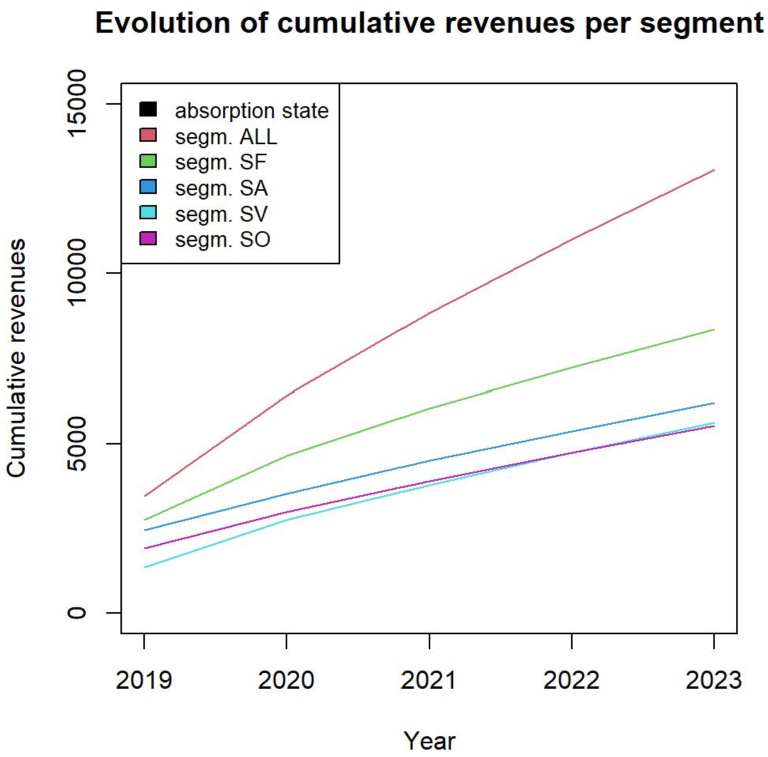


Evolution of profitability by segment

We used the estimated average profitability per segment in 2019 to compute the **trajectory of predicted cumulative revenues by year** (following the Markov Chain)

The **measure of profitability used** is total donation amount minus variable cost (85 cents) for each solicitations sent in a given year, which has then been cumulated over the years

The analysis gives a clear perspective about the **differences in profitability**: the most flexile segment (Trend Setters) gives 56% more revenues than the second most profitable segment (SF focused, the most present segment in 2019 at 27%)



Transition matrix Year on Year (from 2019-2020)

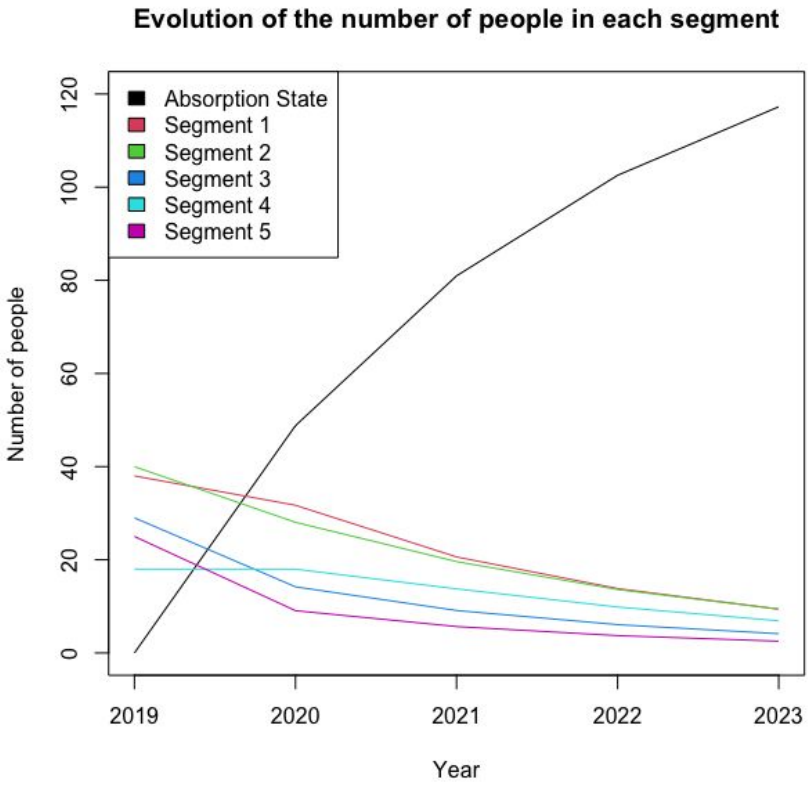
How do segments behave year on year? Our users are currently grouped by their donation behavior, who donates to whom. Some users may be willing Here we assume an absorption state that can not be left.

	Ø	ALL	SA	SO	SV	SF
Ø →	1	0	0	0	0	0
ALL →	0.37	0.26	0.13	0.11	0.05	0.08
SA →	0.42	0.12	0.25	0.05	0.1	0.05
SO →	0.24	0.24	0.14	0.17	0.14	0.07
SV →	0.11	0.17	0.28	0.06	0.39	0.00
SF →	0.36	0.28	0.16	0.08	0.04	0.08

Evolution of segment size

From the 150 people that initially donated in 2019, 117 end up in the absorption state in 2023 if we use the transition matrix computed before.

The segment numbers are as displayed in the previous slide.



How many people to solicit

Dealing with lost customers

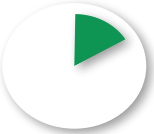
In 2019, out of 161,000 distinct people solicited, 25,000 actually donated (15%). Of these 25,000 people, we expect half to not donate in 2023

However, we saw that there is a 24% chance that they will donate again the following year. Global efficiency is only 15%. It is therefore **reasonable to keep engaging with people that did not donate in a given year**

The **budget that can be saved** by a targeting based on known values/timing of active donors could then be **redirected** to donors that did not manifest themselves in a given year

2023 donors based on 2019 segments

Using a **naïve approach**, we assume based on our initial segmentation that users that vastly cared about some campaigns in particular, should be contacted **specifically** for those campaigns



15%

Trend setters

Contact for:

SA23
SJ23
SO23
LAL23
SF23
SA23

10%

SF focused

Contact for:

SF23
LAL23
SJ23

7%

SA focused

Contact for:

SA23
SV23
LAL23

8%

Strong heads

Contact for:

SV23
LAL23

7%

Loners

Contact for:

SO23

Solicitation by campaign

Some campaigns are worth soliciting far more than others

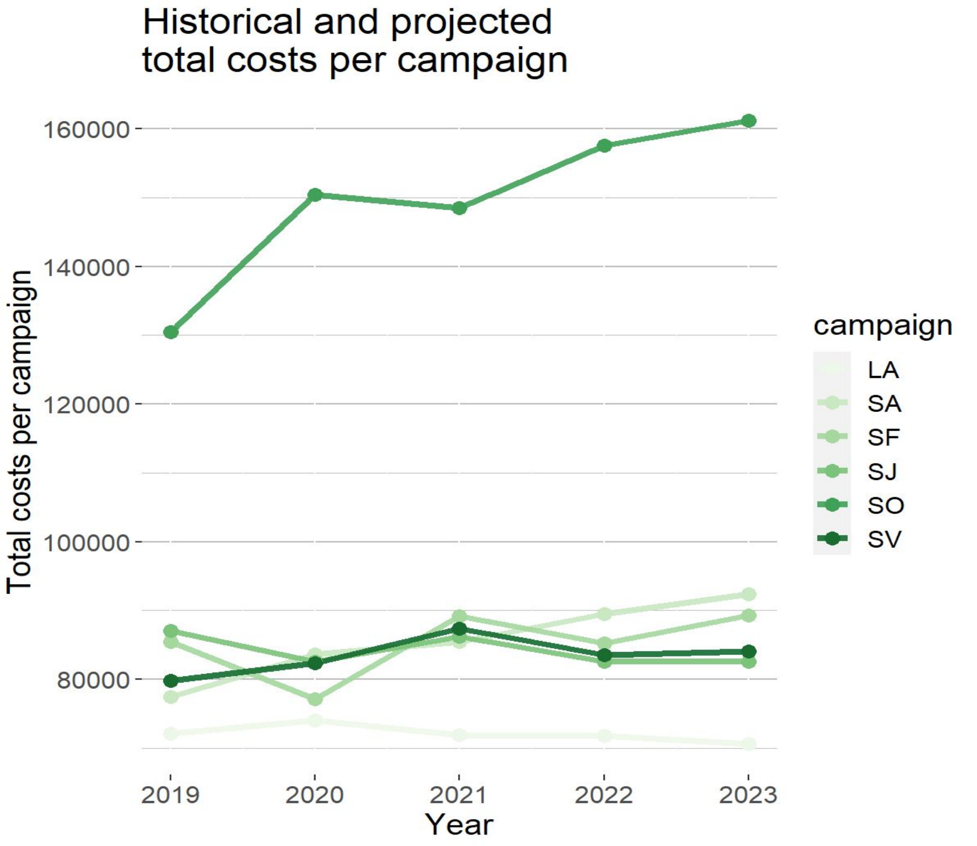
LAL23	SO23	SA23	SJ23	SV23	SF23
46,425	44,950	49,375	46,425	61,175	59,700

Based on our transition matrix we estimated **proportions of the different segments to target** (the table shows the estimated number of solicitations to send).

Specifically, we **decomposed** into segments those that donated in both 2019 and 2020, those that donated in one of the two and the 135,000 lost from the beginning

In particular, for the latter case we expect 50% of them to be in the absorption state, 15% of them to possibly be trend setters etc… based on inference from historical data that goes back further than 2019

Historical and proj. costs per campaign .1



Based on the given amount of fixed and variable costs and historical solicitations, we **projected** the (remaining 2022) and 2023 campaigns. We used the average of a rolling window over the two most recent years

It is evident the **imbalanced** proportion attributed to the SO campaign in October, which could be clarified

Historical and projected costs per campaign

/€	Projected (historical)	Projected (recommendations)
SJ →	82,560	54,461
SF →	89,249	65,745
SV →	84,093	66,998
SA →	92,413	56,968
SO →	161,175	53,207
LA →	70,618	54,461

The table report the projected costs for the 2023 campaigns, both based on historical data (taking the trend) and on our recommendations.

It is clear that additional information are required regarding why certain decisions are made, but our predictions lead to a more **balanced** situation that hinges on the analysis of donation behaviour

The **costs savings** induced by our analysis would be around 40%, passing from 58,0109 € (historical) to 35,1842 € of total required budget for the year

Budget cuts

Some years, the charity may experience **budget cuts.** In this scenario, we recommend following the following pecking order of segments:

01

Trend setters are more likely to respond than any other segment, and showcase the highest profitability out of our 5 segments

02

Period donors whose past behaviour can give information about shared values/habits for donations that can be a based for punctual targeting

03

The average efficiency with people that donated in 2019 but are now **no longer donating**, is higher than the global efficiency. These people should be prioritized afterwards.

Bonus analysis: Peer to peer donors

- In **traditional network analysis**, it is important to find influential nodes (influencers) that can spread the message for your campaign. In our definition, these influencers are not immediately identifiable.

- However, we believe the charity can gain by complementing their solicitations with the inclusion of a **testimony from a 'persona'** of each segment.

- We can for example interview some donors in each segment, and ask them what **attracted** them to a certain campaign. This can be used in the next campaign of this type to give other people that are solicited something they can relate to.