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Tackling toxic content

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Elastic

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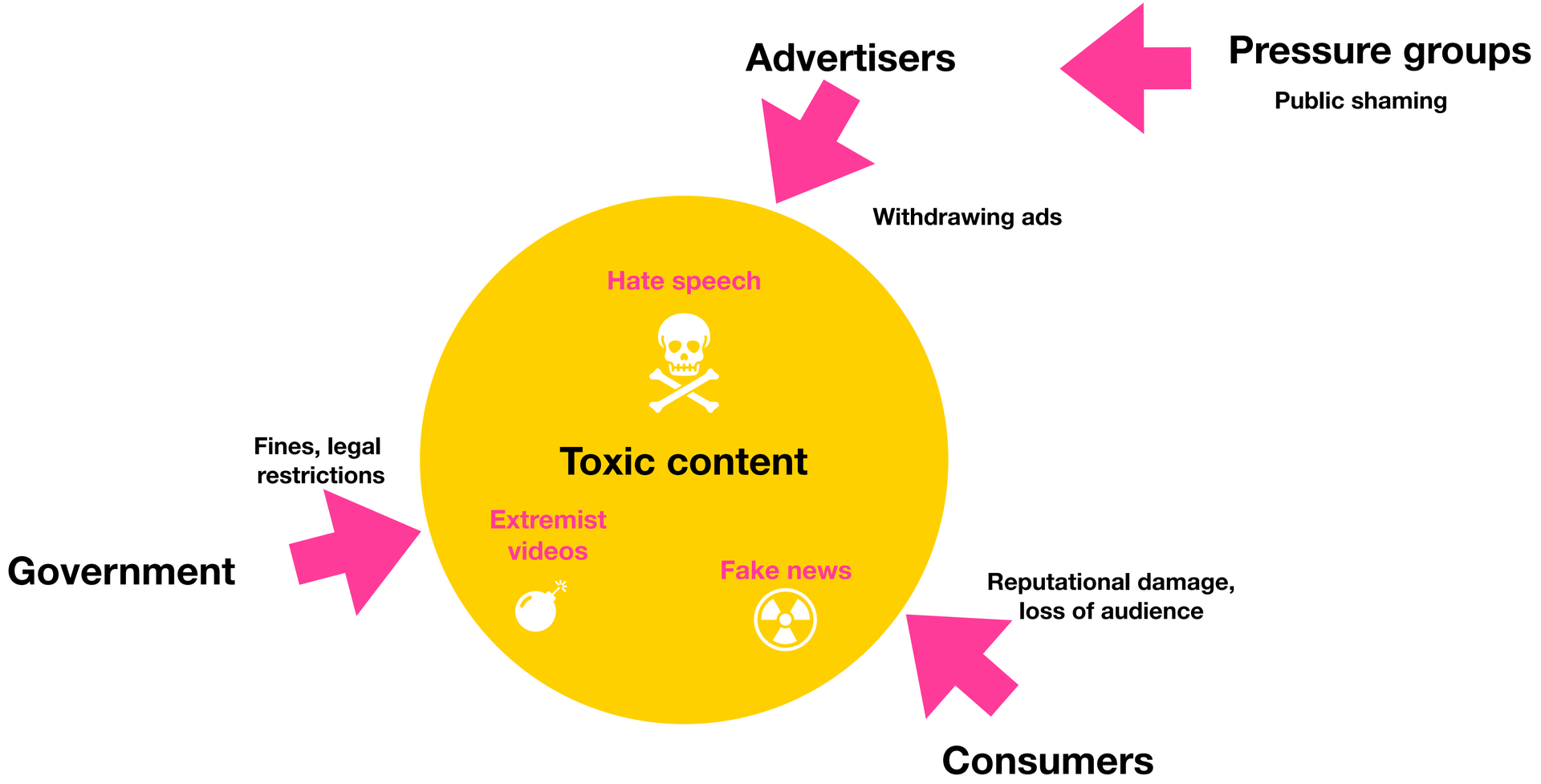
@elasticmark

Business drivers for tackling toxic content



How?

Two approaches:

- **Proactive**
  - Root out content before it gathers an audience
- **Reactive**
  - Respond to complaints from the audience

How do your staff determine what is “toxic”?

Whose opinions do you trust?

Proactive challenge

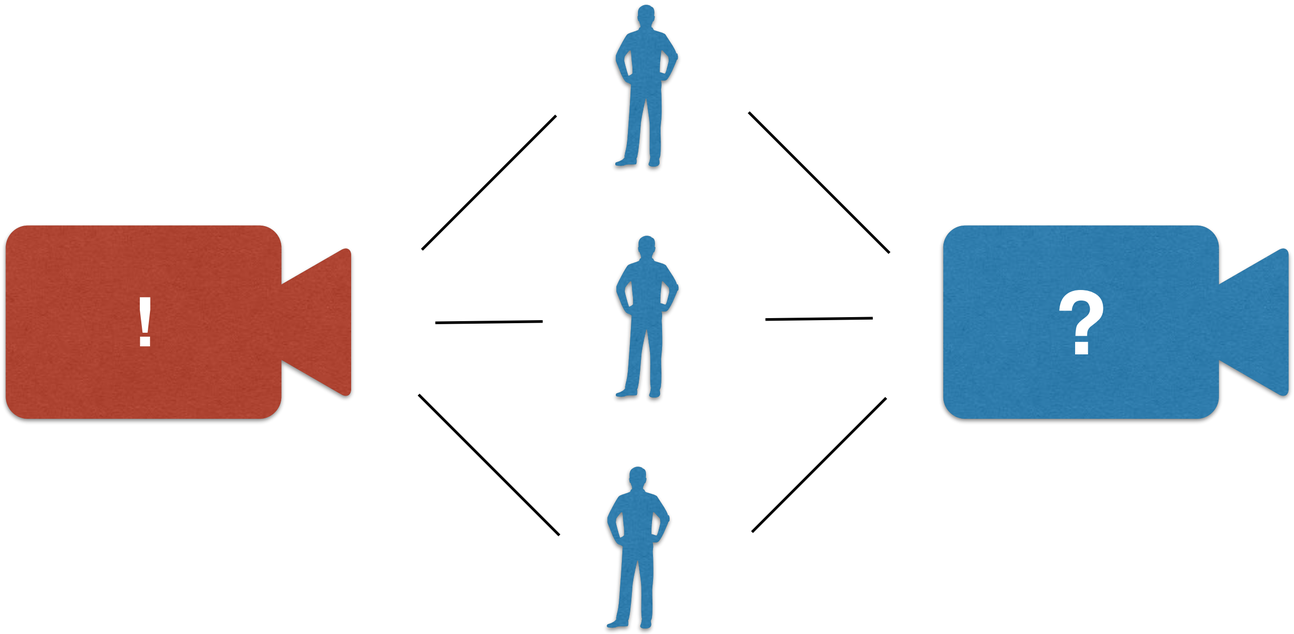
How do we determine what is toxic?

Content based analysis is hard

- **Parsing is hard** - content is often binary e.g. audio or video
- **Limited metadata** - lack of descriptions or keywords

Easier to examine activity around content

- Reuse the basis of recommendation engines - people who liked X also like Y



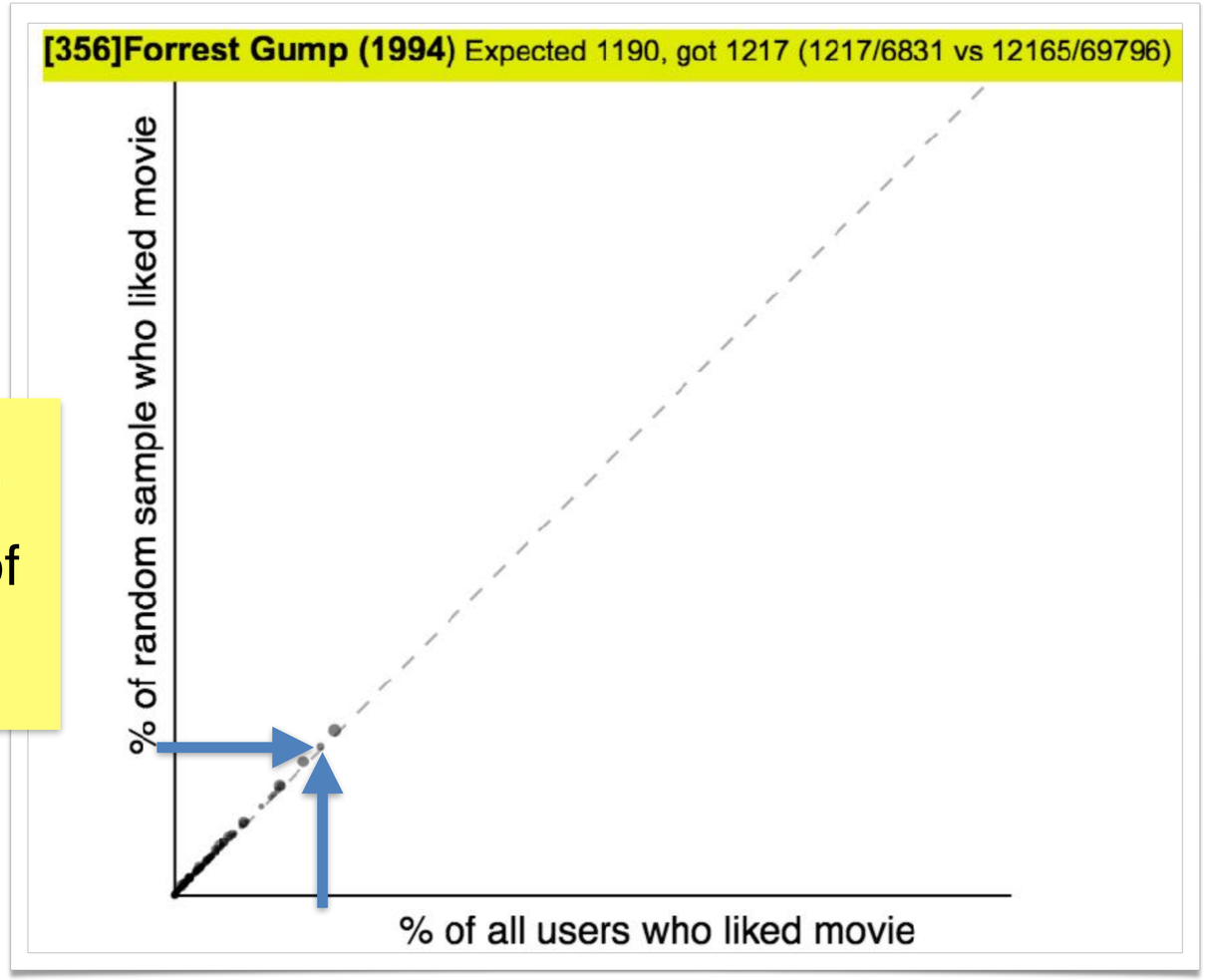
Recommendations recap: MovieLens data

```
{
    "movie": [260, 500, 1080...]
    "user": 8353
}
```

http://files.grouplens.org/datasets/movielens/ml-10m-README.html

Random samples should hold no surprises

- 17% of all people like “Forrest Gump”
- In a random sample of people, 17% of them will also like “Forrest Gump”



Dull. But in non-random samples something interesting happens…..

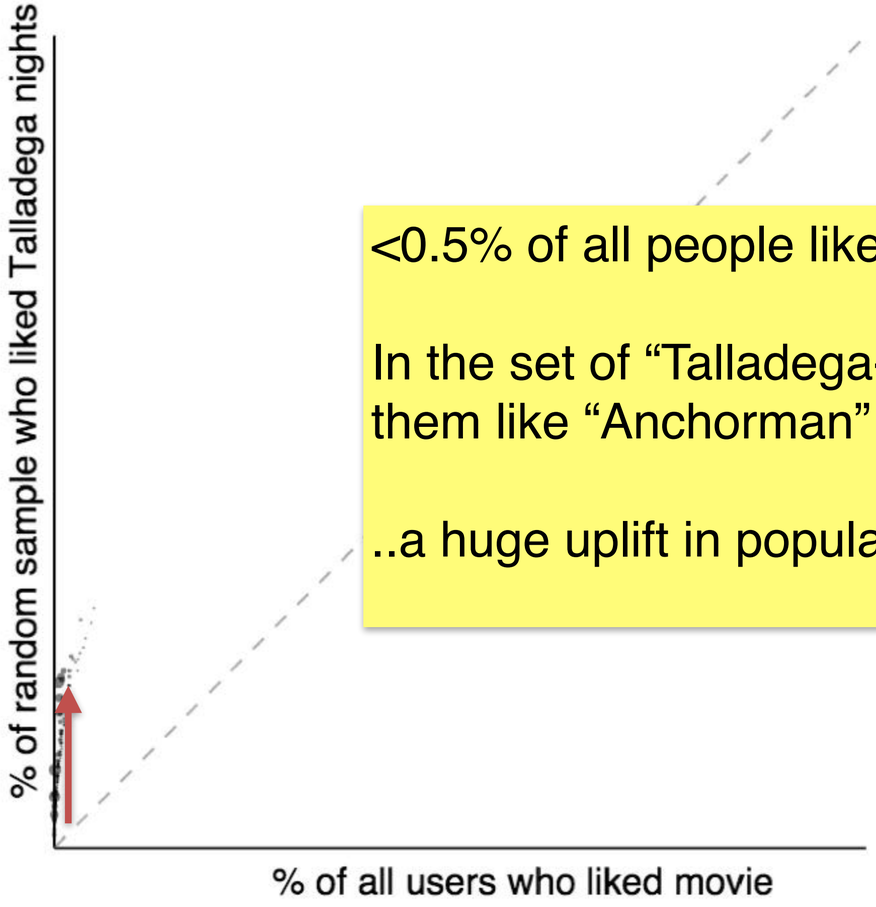
Non-random sample: people who liked “Talladega nights”

Find all people who liked movie #46970

```
{
    "query" :
    {
        "terms":{"movie": [46970] }
    },
    "aggs" : {
        "keywords": {
            "significant_terms": {
                "field": "movie",
                "size": 50
            }
        }
    }
}
```

Summarise how their movie tastes differ from everyone else

[8641]Anchorman: The Legend of Ron Burgundy (2004) Expected 1, got 55 (55/271 vs 374/69796)



<0.5% of all people like “Anchorman”

In the set of “Talladega-likers”, 20% of them like “Anchorman”

..a huge uplift in popularity from the norm!

Proactive demo

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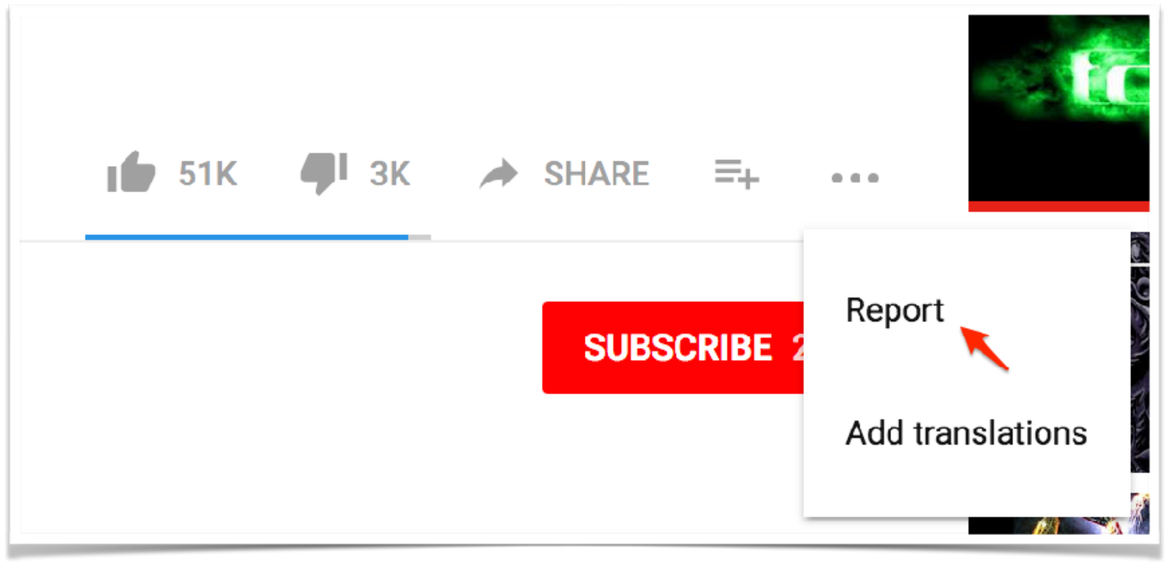
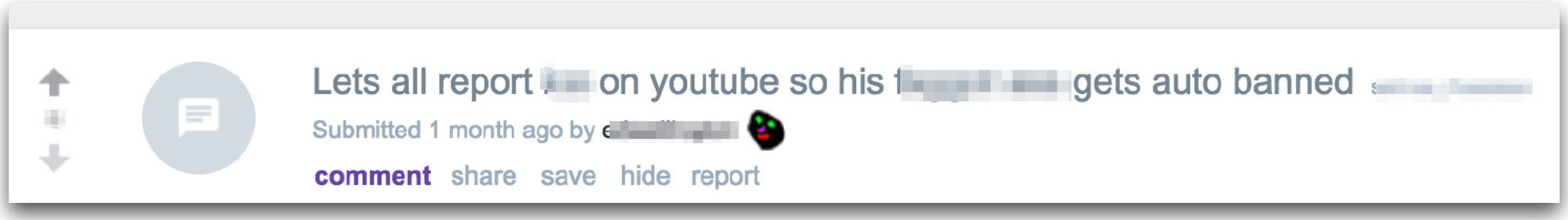
Reactive challenge

Whose opinions do we trust?

Allow end users to report toxic content



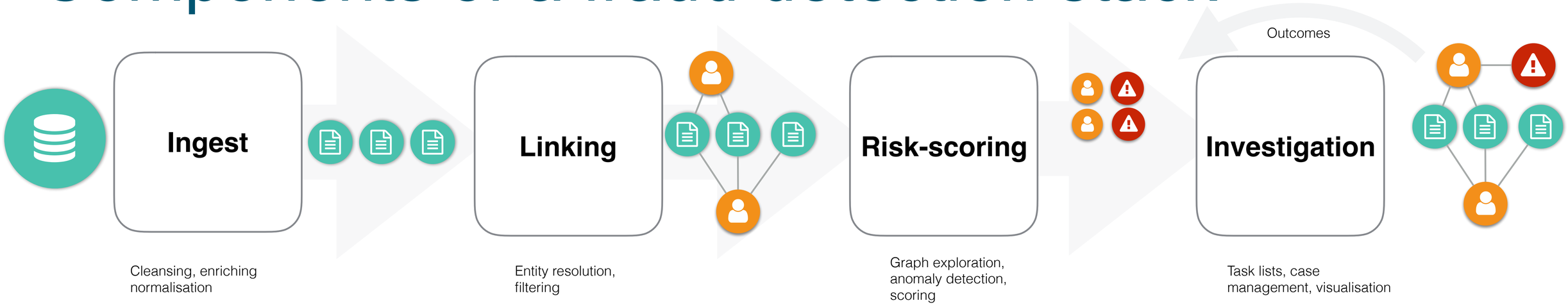
BUT - some user reports, like some content, can be questionable



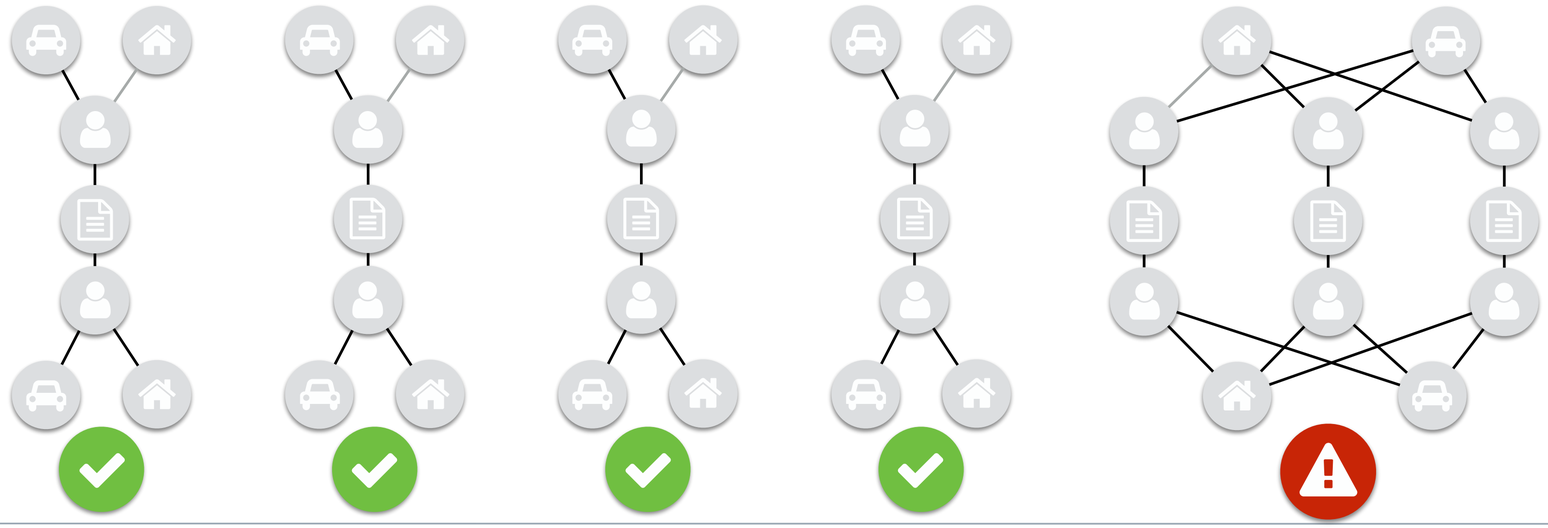
Review fraud is a thing

- **Positive reviews** - “shill” or “sock puppet” accounts are used to artificially inflate the reputation of sellers in a marketplace
- **Negative reviews** - fake accounts or mob-rallying is used to sabotage the reputation of an innocent party.
- Tell-tale signs of collusion might include:
- - A common IP address or user agent
- - A common "hit list" of items being flagged
- - A common phrase used in feedback
- - The same time-of-day when logging requests
- - The same site join-date

Components of a fraud detection stack



Bad actors make strange shapes



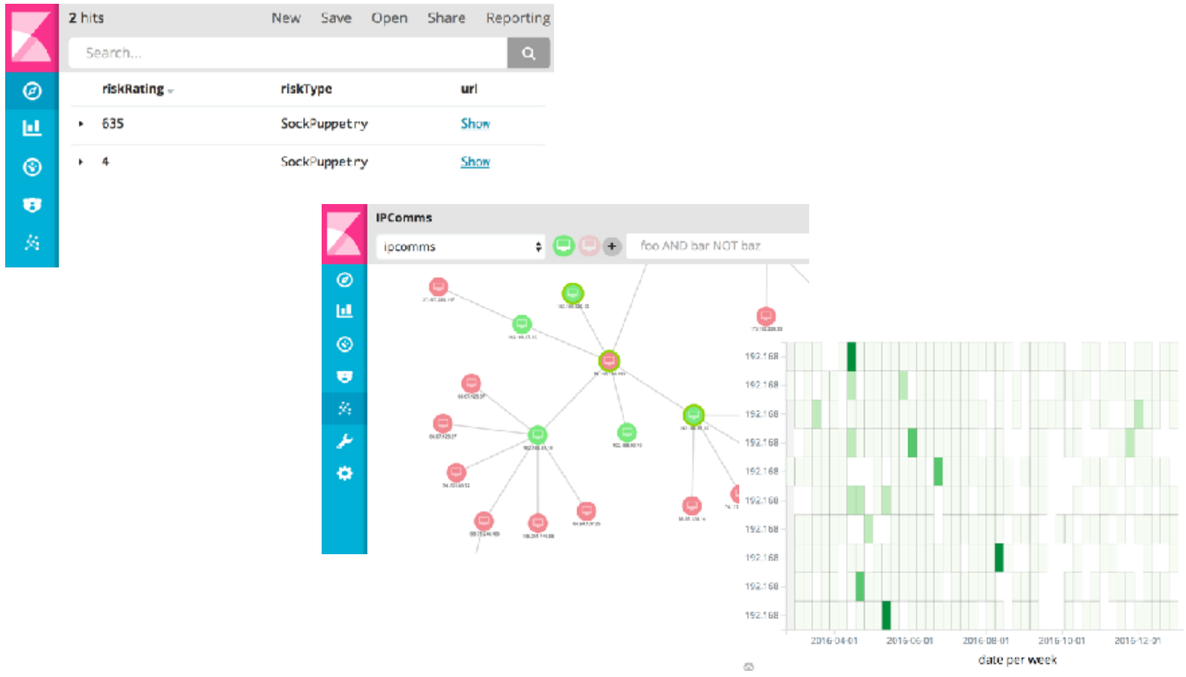
It is hard for identity manipulators to avoid reusing resources (IP addresses, join dates, subject lists, phrases, time) .

Fraudsters generate too many “coincidences”.

Use the Graph API to gather related data then raise alerts on anomalies.

See example: http://bit.ly/es_fraud

Responding to alerts



Kibana with the Graph plugin allows investigators to examine details behind alerts.

See example: http://bit.ly/es_fraud

Demo