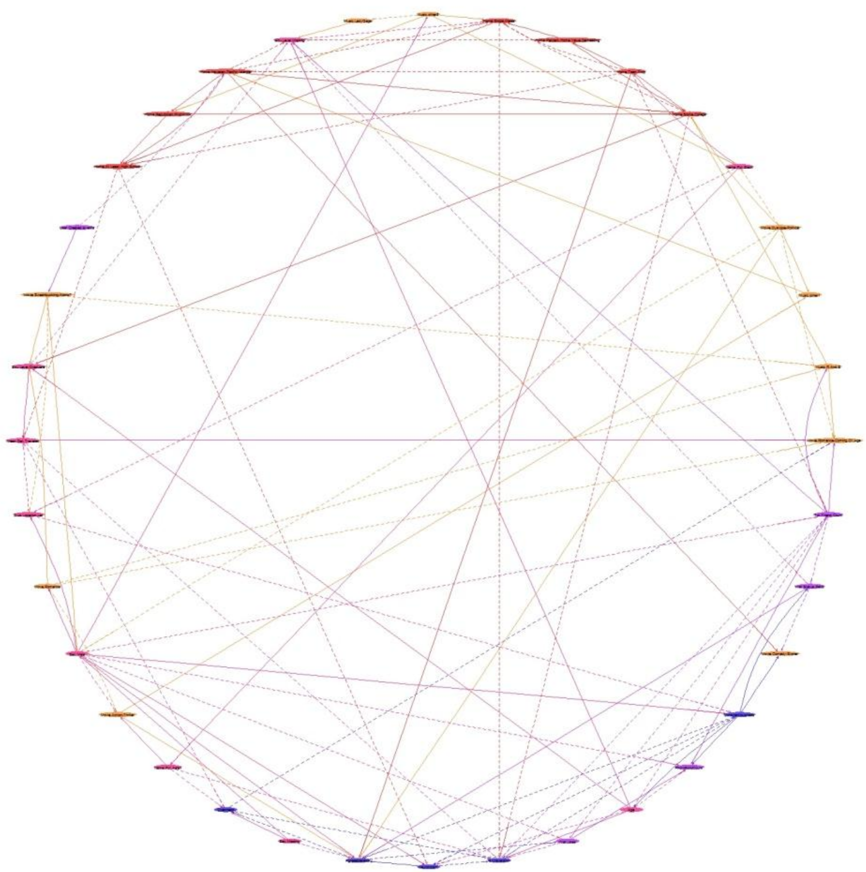
Leveraging online social network data and external data sources to predict personality

Daniel Chapsky



Overview

- Personality can be expressed through actions online, especially on online social networks (OSNs) like Facebook.
- Data on OSNs can be connected to external data sources for further inference.
- Machine learning to connect networks of information to predict personality
- Framework which can learn about the inferences as well as develop predictions

Overview - Steps

- Collect personality data on a sample
- Collect Facebook data of the sample
- Mash up Facebook data with external APIs to infer attributes, behaviours and culture of sample
- Generate a machine learned model which predicts personality through inferences

Tools

- An online personality quiz
- Collected Facebook data
- Online Data Sources
- Revolution R Enterprise version 4.0 (for academics)

R

- All steps besides quiz done in R
- Database connectivity
  - RMySQL,
- Web scraping / API connection
  - RCurl, RJSONIO, XML
- Inference through mashups
  - psych, geosphere

R Continued

- Data Cleaning
  - plyr, reshape2, bayestree, mice, tm, mvoutlier
- Bayesian Network construction
  - bnlearn, pcalg
- Parallelization of optimization
  - foreach, snow
- Graphics
  - Latticist, bnlearn, ggplot2

Personality

- Personality is the collection of behavioral and mental attributes that characterize an individual
- Actions and perspectives are considered expressions of underlying personality
- A portrait of an individual's personality can be captured by combining his/her
  - Attributes
  - Culture
  - Behaviors

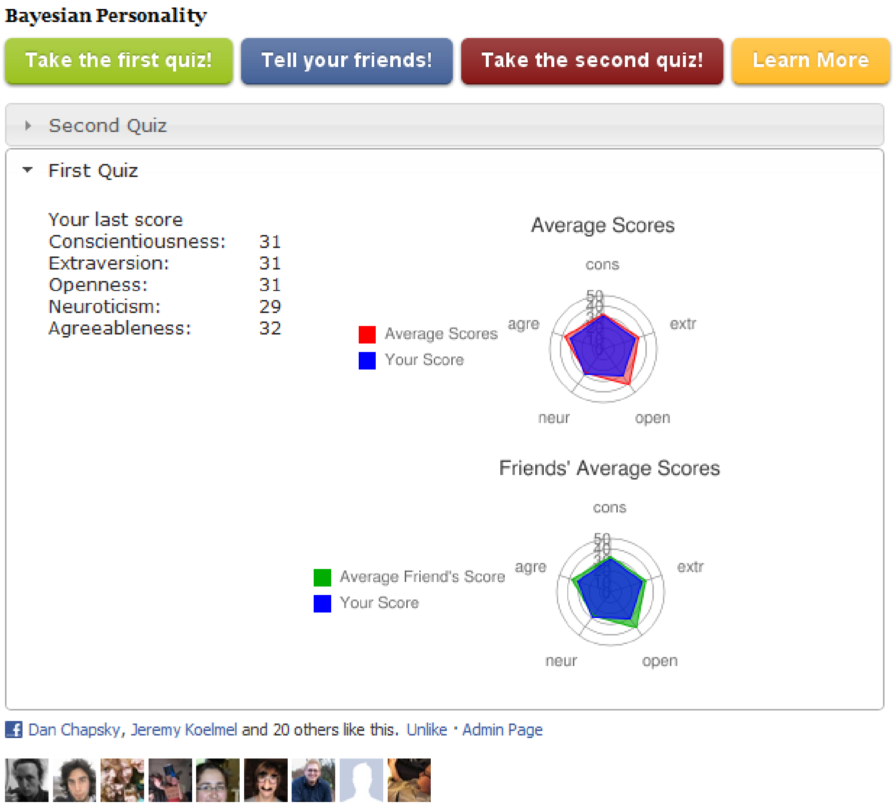
Personality - Big 5 Theory

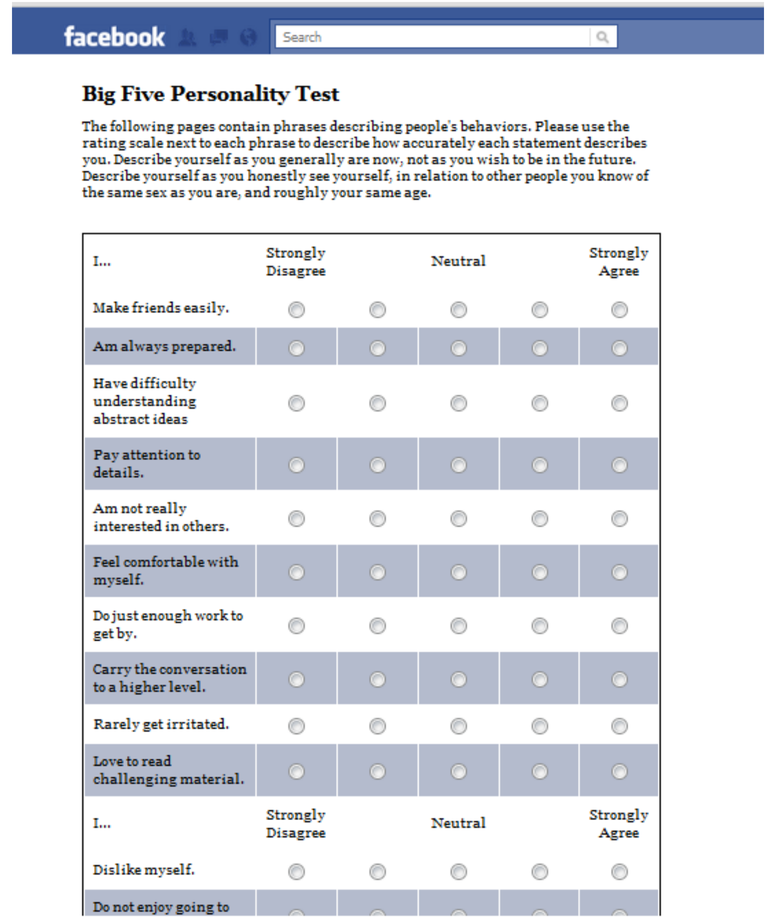
- Personality can be largely described by 5 personality factors
- The five factors compose a 5 dimensional personality space.
- Knowledge of these factors can be used to predict the attributes, views and behaviors of an individual

Personality – 5 Factors

- Neuroticism
  - Anxiety, Impulsivity
- Extraversion
  - Energy, stimulation through company of others
- Openness (to experience)
  - Academic curiosity, highly correlated with liberal political leaning
- Agreeableness
  - Compassion, desire for social cohesiveness
- Conscientiousness
  - Discipline, organization, motivation

Personality - Quiz Page

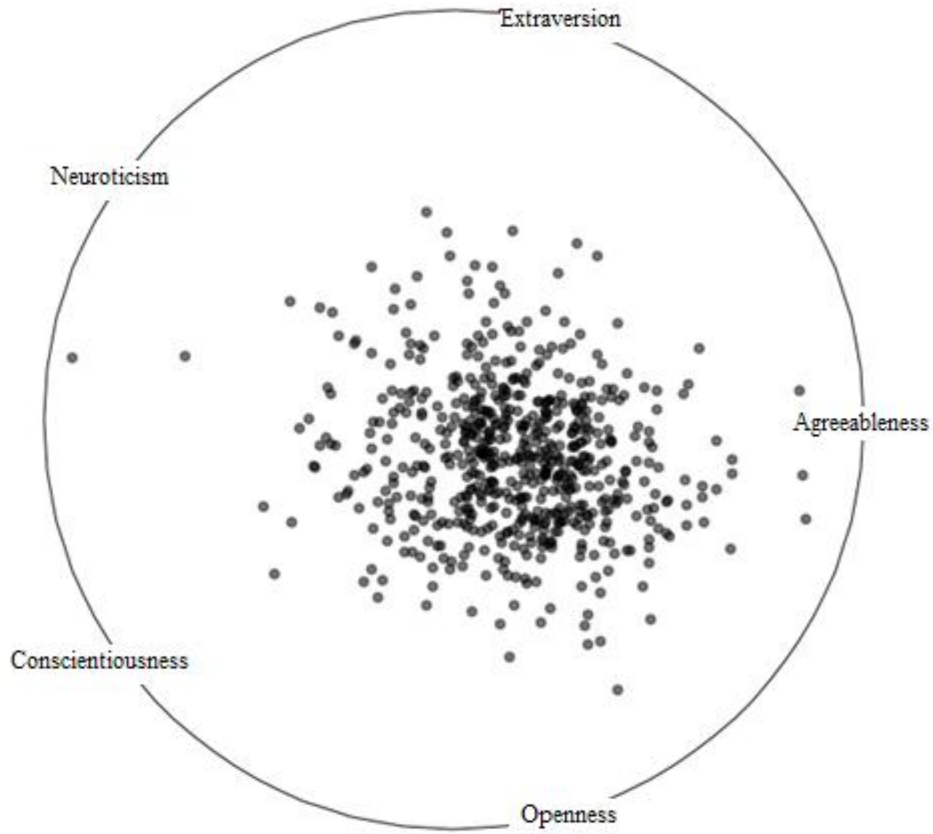




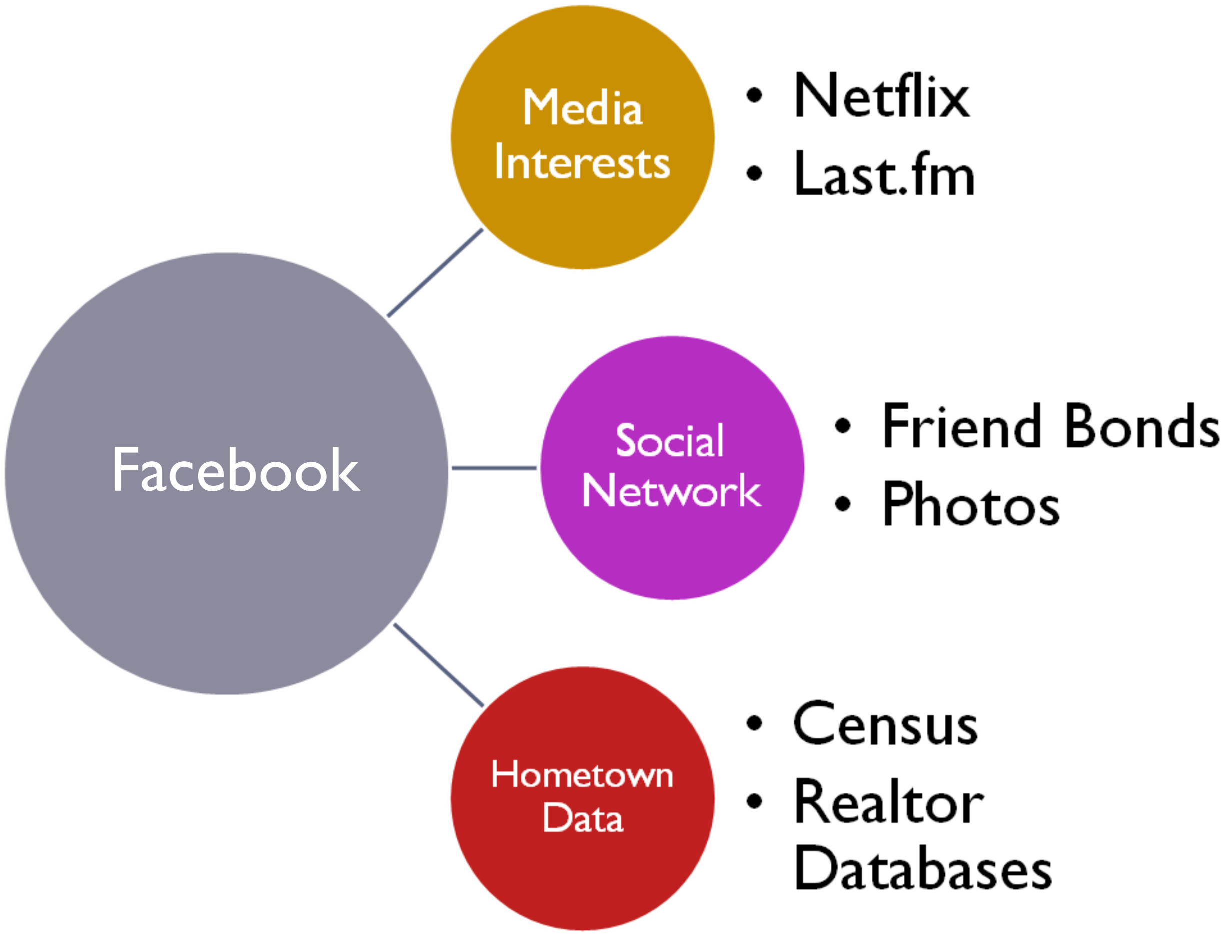
Personality – Quiz Results

- 100 Question IPIP NEO-P-R
- Factor score 0- 50 scale
- 615 Respondents
- 35% Hampshire College students
- 35% Friends of Hampshire College students
- 30% recruited from online ads
- Skew towards politically liberal and middle class

Personality - Quiz Results



Inference


Facebook
Media Interests
Social Network
Hometown Data
• Netflix
• Last.fm
• Friend Bonds
• Photos
• Census
• Realtor Databases

Inference - Media Preferences

Movies

- Netflix Data
- Preset list of possible genres
- Movies assigned Genres by Netflix
- 2100 movies analyzed

Music

- Last.fm data
- User generated tags
- Using tags voted on to be most popular
- 7500 bands analyzed

Libraries : RMySQL, RCurl, RJSONIO, XML

Inference - Media

Sample Music Factors

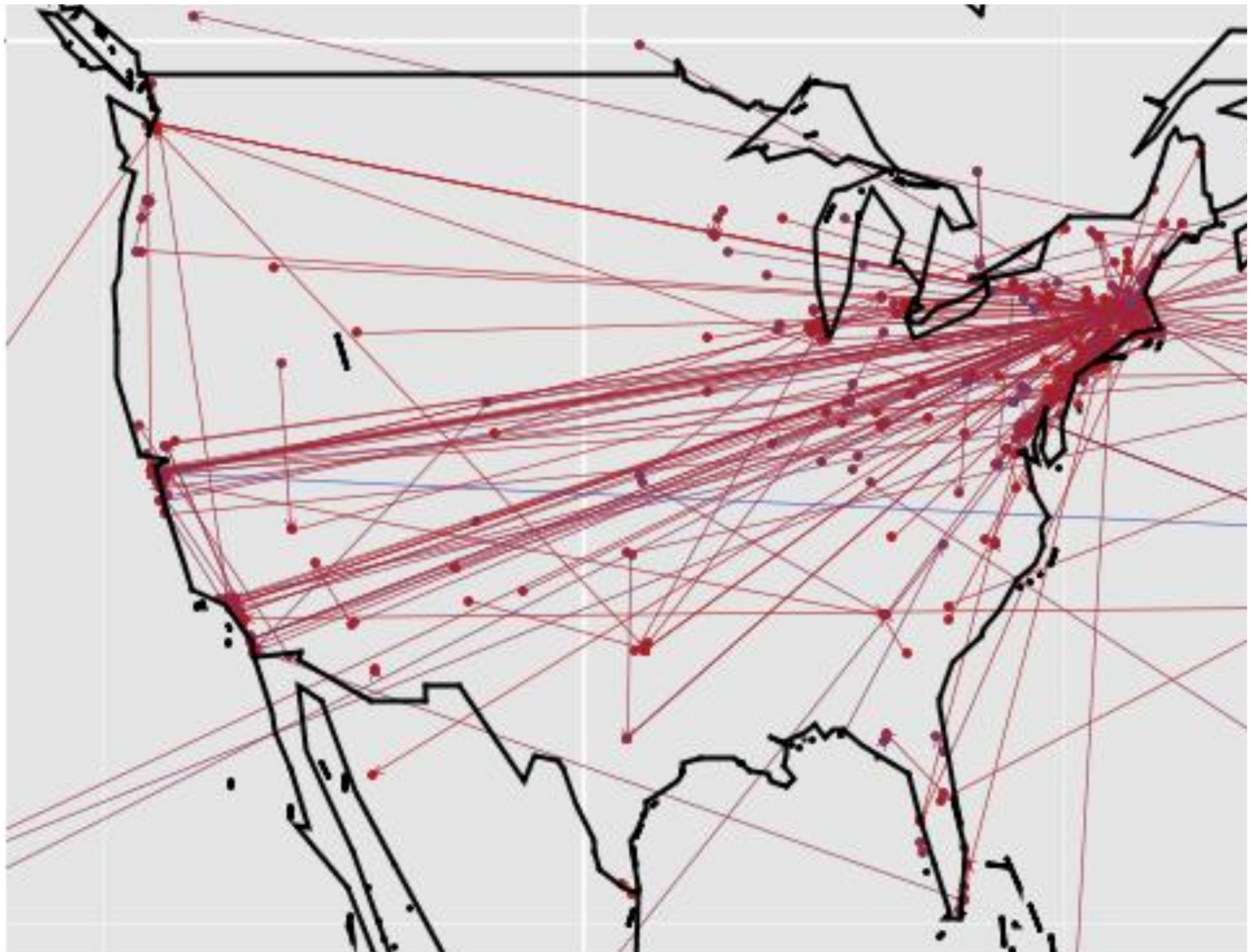
- Rock-80s
- Rap
- Metal
- Lady Gaga

Sample Movie Factors

- Action-Thriller
- Horror-Supernatural
- Dystopia-Political
- Romance

Libraries : psych, mice

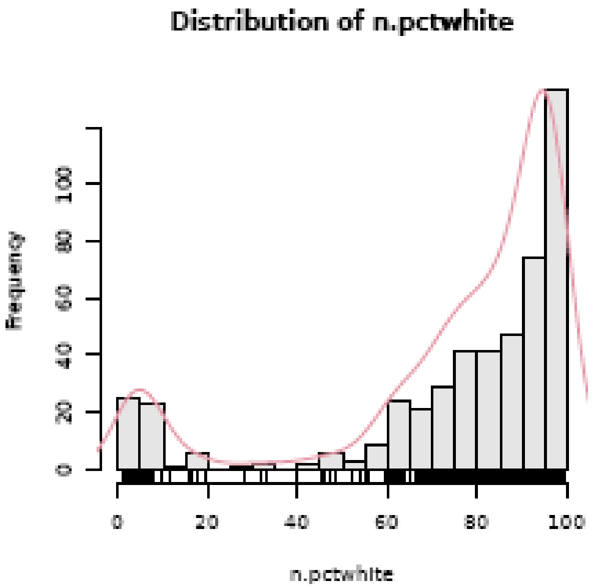
Inference – Distance Traveled

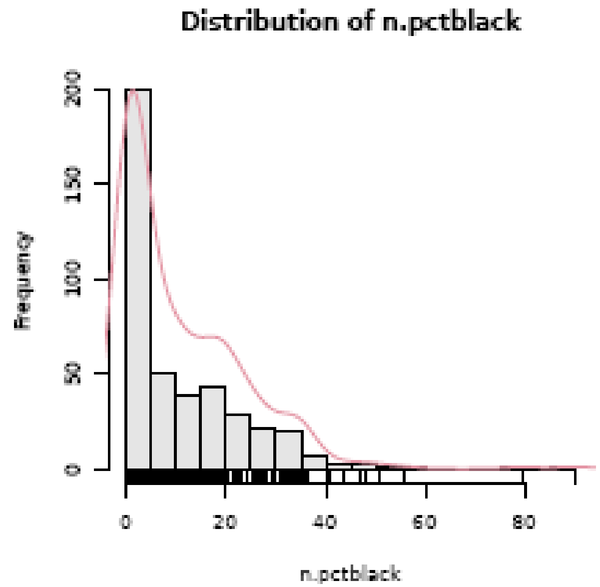


Libraries :
ggplot2,
geosphere,
maps

Inference - Race

name	rank	count	prop100k	cum_100k	white	black	api	aian	2prace	hisp
SMITH	1	2376206	880.85	880.85	73.35	22.22	0.4	0.85	1.63	1.56
JOHNSON	2	1857160	688.44	1569.3	61.55	33.8	0.42	0.91	1.82	1.5
WILLIAMS	3	1534042	568.66	2137.96	48.52	46.72	0.37	0.78	2.01	1.6





(Chang,2010)

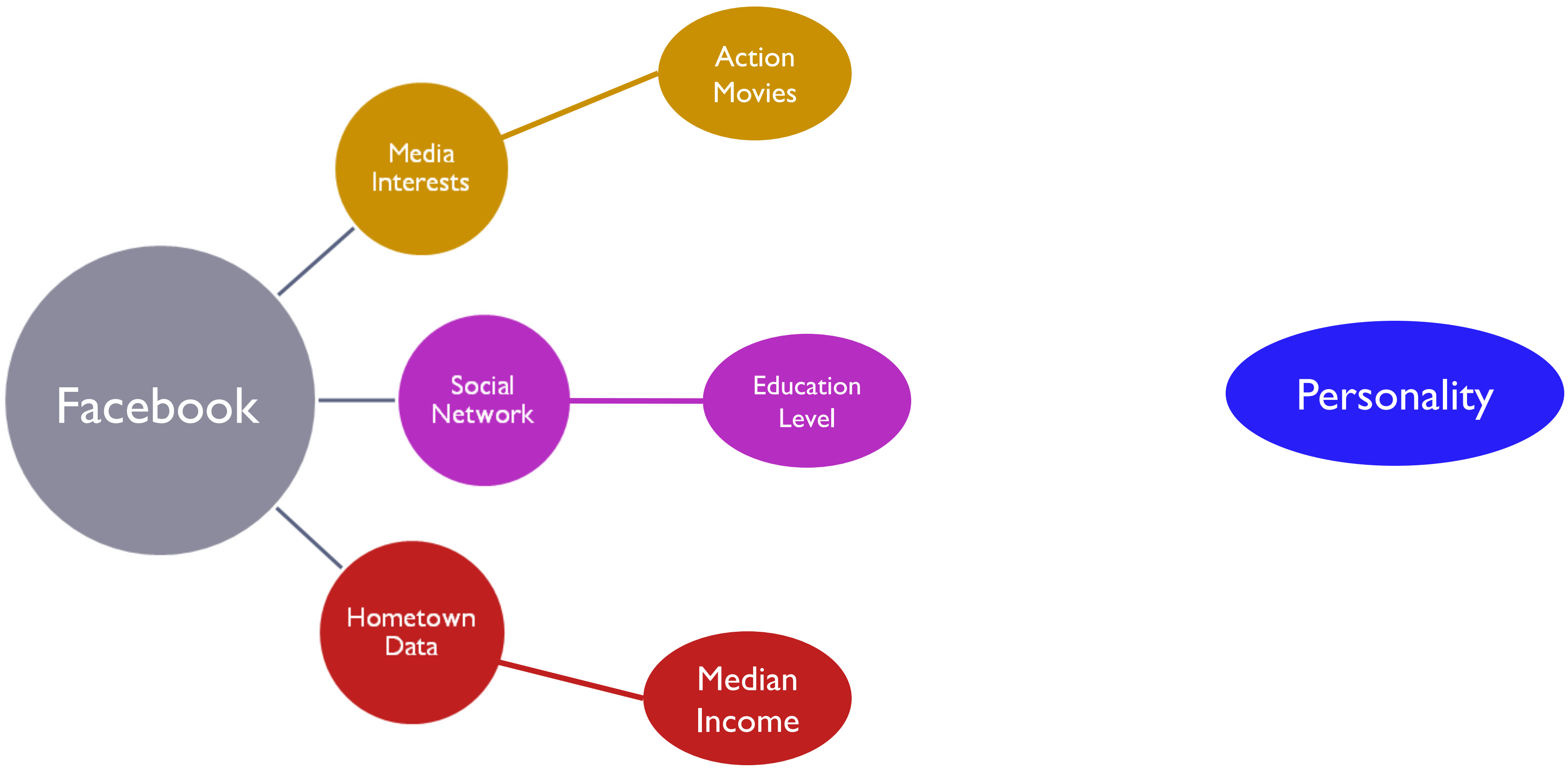
Inferences - Overview

Type	Example variables
Base demo-graphics	Age, Sex, Education level, Geographic location, Ethnicity based on last name
Social Network	Friend count, Social network density,
Hometown Data	Mean income, Average education level
Media Interests	Movie genres such as comedy, romance, dystopia-political,
Behavioral Actions	Distance moved, Amount of Facebook interaction

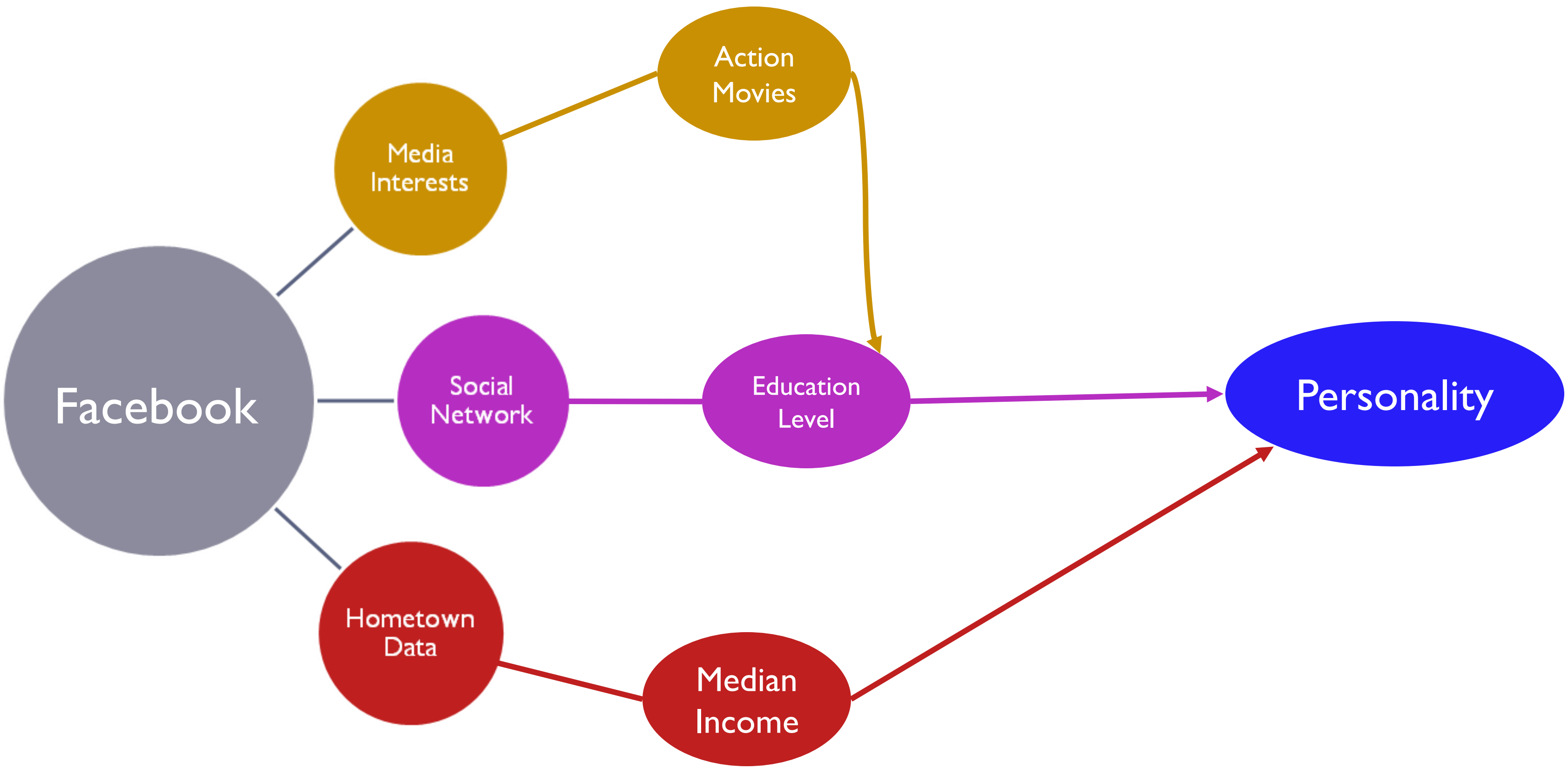
Inference


Facebook
Media Interests
Social Network
Hometown Data
Personality

Inference


Facebook
Media Interests
Action Movies
Social Network
Education Level
Hometown Data
Median Income
Personality

Inference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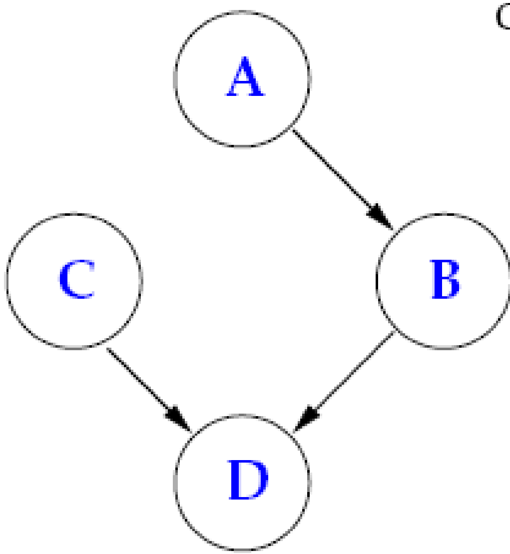
Bayesian Networks

- Directed graphical models representing joint probability distributions
- Edges represent conditional relationships
- A parent is related to its children and its children's children



CPT of B

	A='F'	A='T'
B='F'	0.23	0.6
B='T'	0.77	0.4

CPT of D

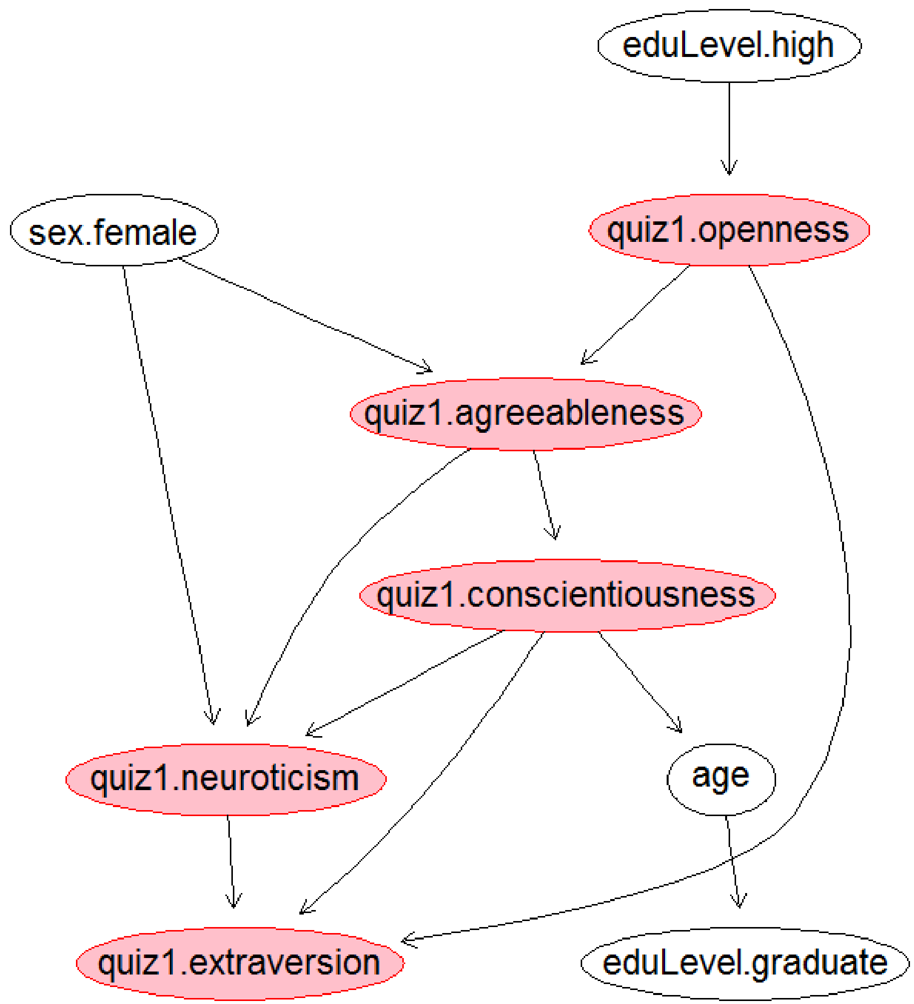
	B='F', C='F'	B='F', C='T'	B='T', C='F'	B='T', C='T'
D='F'	0.65	0.54	0.78	0.01
D='T'	0.35	0.46	0.22	0.99

(Wong, 2004)

Bayesian networks

- Allow straightforward inference
- Belief propogation for limited evidence
- Clear underlying semantics
- Often have weaker predictive power than “black box” prediction methods

Bayesian Network - Example

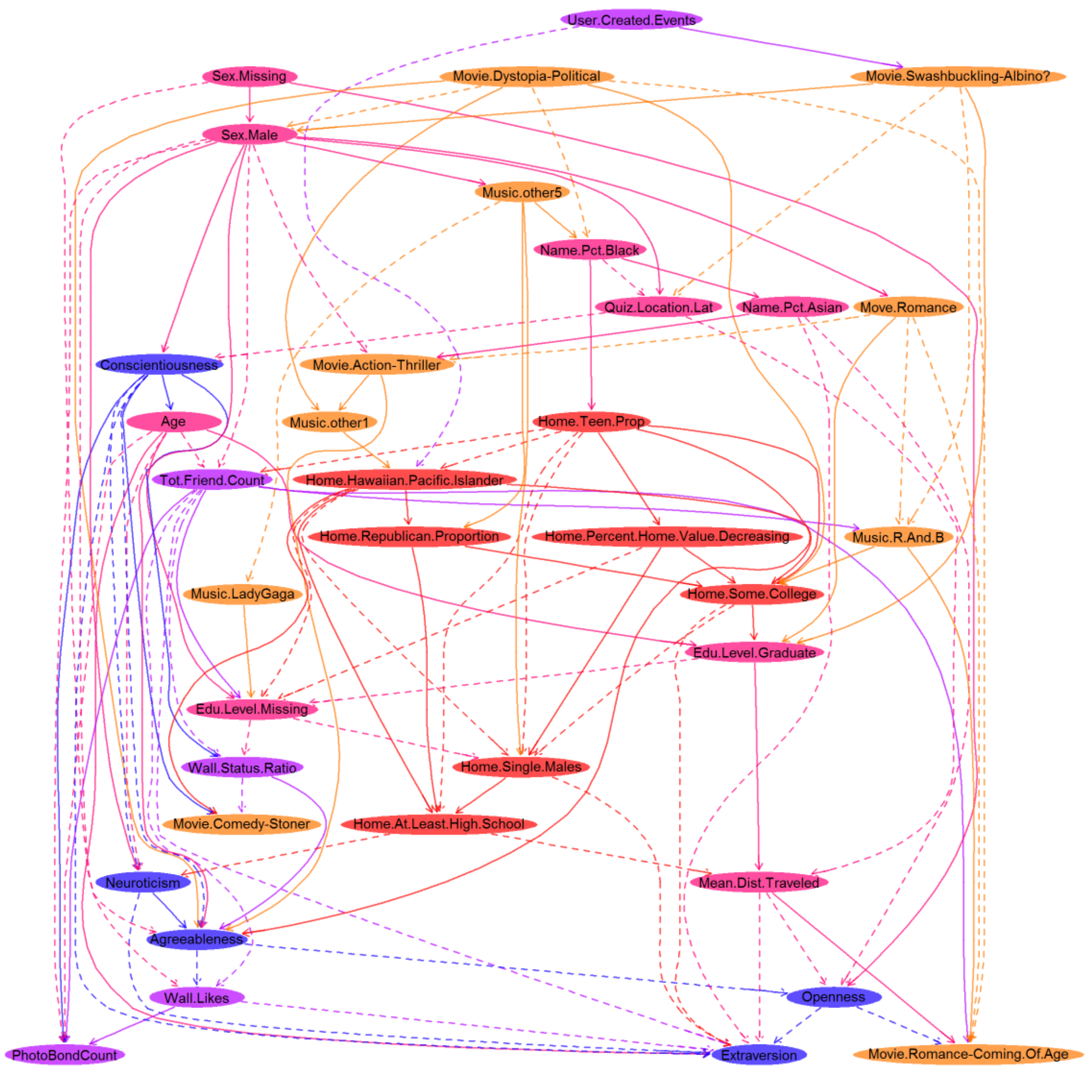


Bayesian Network - Construction

- Primary goal maximizing predictive power of models on personality
- Continuous data + dummy variables
- Genetic algorithm used for variable selection
- Cross validation to prevent over-fitting
- Missing variables imputed with gibbs sampling
- Model's were assessed on the summed $\mathbf{R}^2$ of all 5 personality factors.
- Hybrid Bayesian Network construction used with the grow-shrink algorithm and hill climbing
- MLE for parametization of Network

Libraries : mice, bayestree, genalg, bnlearn, snow, foreach

Results – Current Model



Color By Source

Personality Data

Facebook Data

Hometown Data

Media Data

Positive Relationship

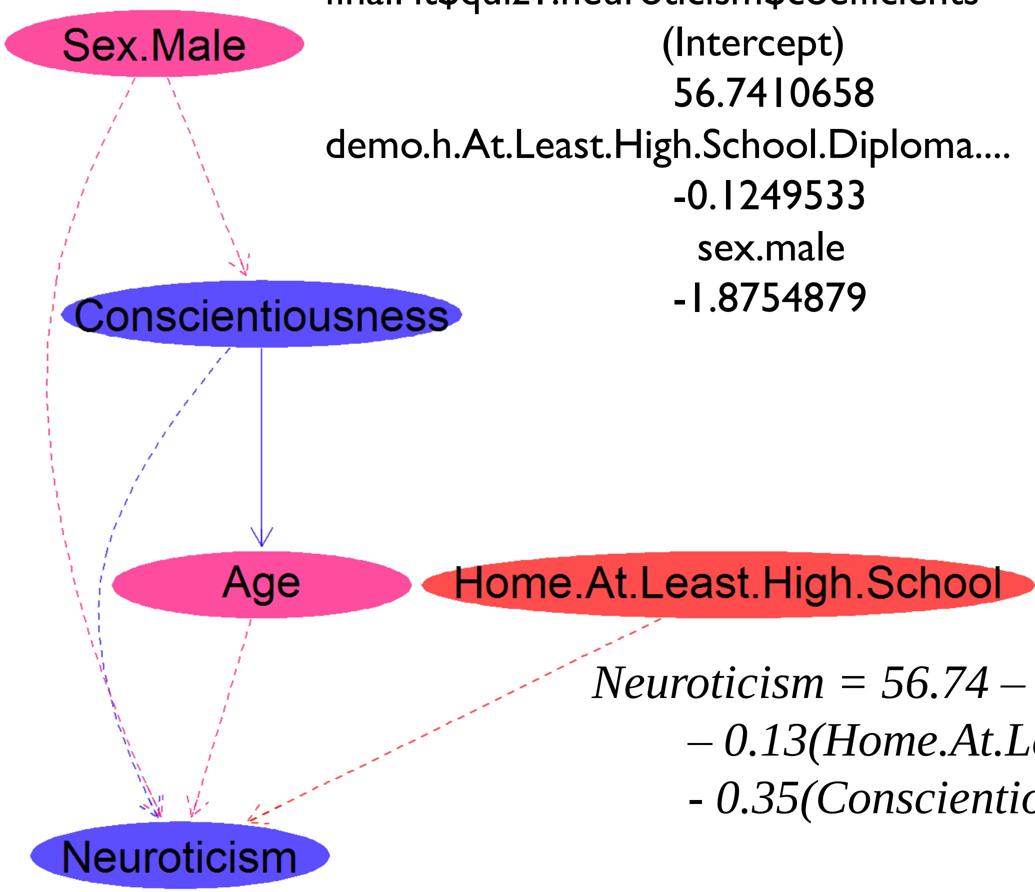
Negative Relationship

Libraries : RGraphviz

Results - Neuroticism

finalFit$quiz1.neuroticism$coefficients

(Intercept)	age
56.7410658	-4.4157869
demo.h.At.Least.High.School.Diploma....	quiz1.conscientiousness
-0.1249533	-0.3533682
sex.male	
-1.8754879	



Neuroticism = 56.74 – 4.42(Age)
– 0.13(Home.At.Least.High.School)
- 0.35(Conscientiousness) – 1.88(Sex.Male)

R^2= .35

Results – Extraversion, Openness

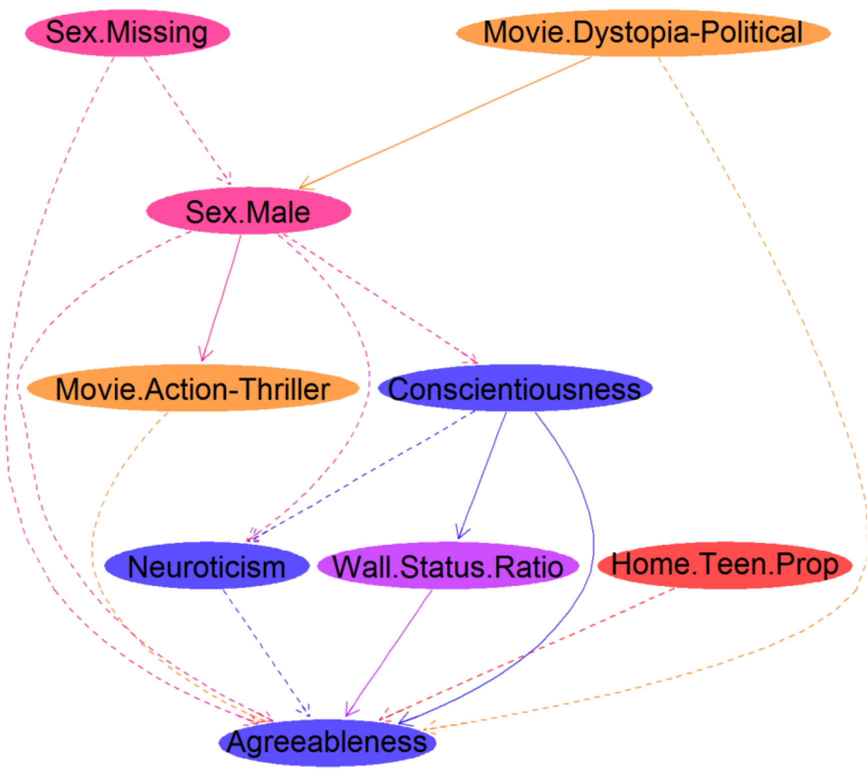
Extraversion = -2.81 - 0.59(Mean.Dist.Traveled) + 4.71(Age)
+ 5.86(Conscientiousness) + 2.49(Wall.Likes)
+ 32.04(Home.Some.College) + 3.76(Home.Single.Males.city)
+ 0.15(Conscientiousness) + 0.29(Openness)
- 0.27(Neuroticism) + 1.53 (Name.Pct.Asian)

R^2 = .56

Agreeableness = 42.38988
- 1.26(Sex.Missing) - 0.63(Movie.Dystopia-Political)
- 25.99(Home.Teen.Prop) - 0.49(Movie.Action-thriller)
+ 6.51(Wall.Status.Ratio) + 0.08(Conscientiousness)
- 0.29(Neuroticism) -2.47(Sex.Male)

R^2 = .46

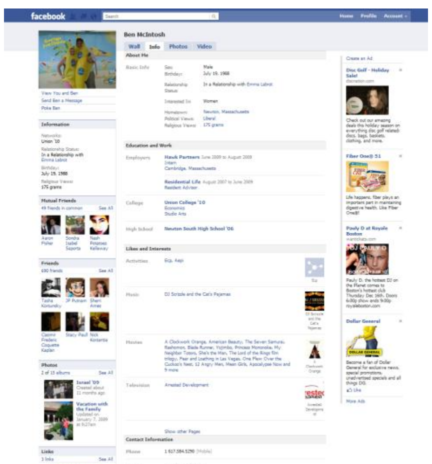
Results - Belief Propogation



- Before evidence is introduced, model assumes marginal probability distribution
- Probability updated with evidence

Results – Belief Propogation

Factor Analysis



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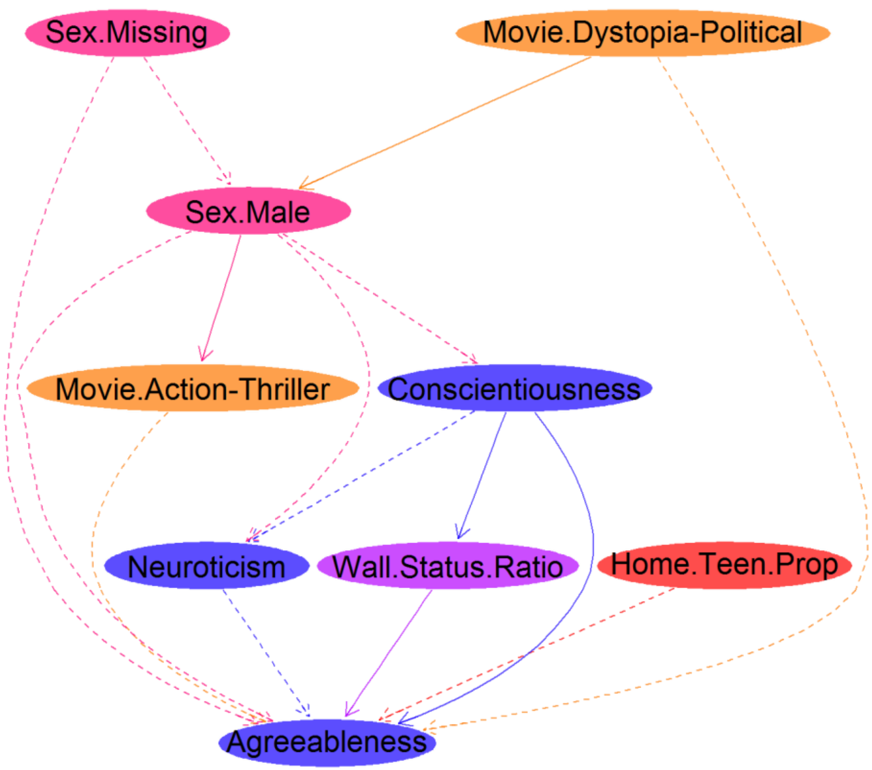
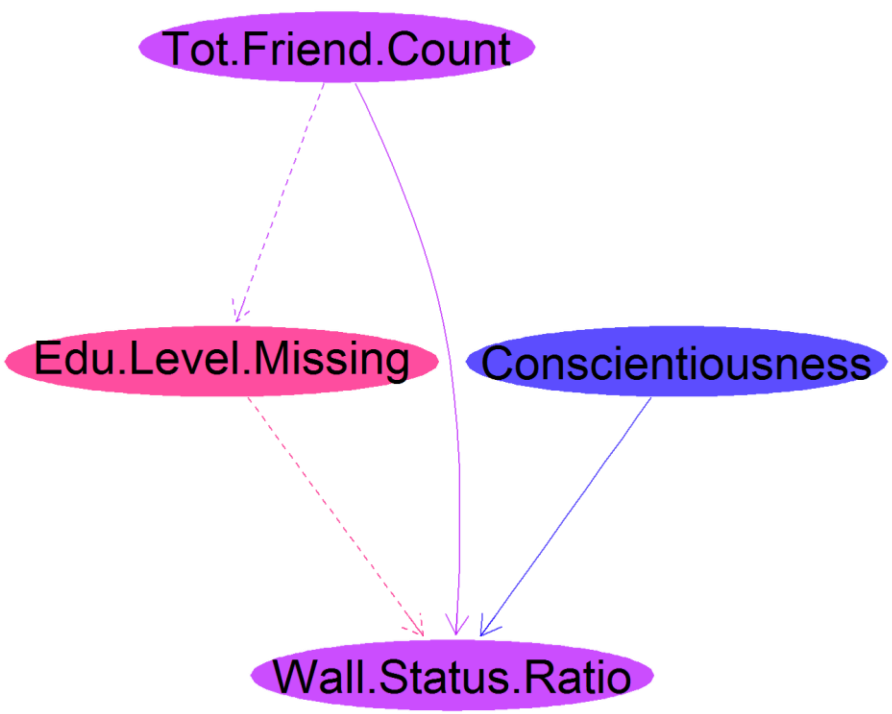
Results - Belief Propogation



- Belief propogation also generates predictions for non-personality variables

Results – Outward Prediction



- Wall.Status.Ratio is a ratio of users status updates vs. how much their friends post on their walls
- His attributes are used to predict actions, which then predict personality

Results – Weakness’

- Large sample size needed for discrete BN construction
- Sample collected from small area
- Relatively low Predictive accuracy

Further Findings

- Other modeling techniques can generate more accurate results
- Similarly, BN models which optimize a single personality measure are significantly more accurate
- SVM : Extraversion R^2 = 0.84
- Single Node Optimization BN: Extraversion R^2 = 0.75

Future Work

- Using personality for outwards prediction
- A larger sample size would allow more conditional inference
- Improving predictions by predicting single nodes at a time
- Using streaming data to update predictions with a Dynamic Bayesian Network
- Could be scaled to constantly update belief about individuals, their personalities and preferences.

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End

- Thanks to :
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- Questions?