Knowledge Inference and Social Class Common Ground

true
Affiliation

as is expensive and burning it is bad for environmental health. How do I choose a car to optimize my gas mileage? We examine a few potential variables to help answer this question.

Study Description and Data Preparation

```
library(readxl)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(writexl)
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v forcats   1.0.0     v readr     2.1.5
## v ggplot2   3.4.4     v stringr   1.5.1
## v lubridate 1.9.3     v tibble    3.2.1
## v purrr     1.0.2     v tidyr     1.3.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(psych)
```

```
##
## Attaching package: 'psych'
##
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```
library(ggplot2)
library(citr)
library(papaja)
```

```
## Loading required package: tinylabels
```

```
# Read data
dataset <- read_xlsx("dataset.xlsx")

# Tidiness check
str(dataset)
```

```
## tibble [87 x 41] (S3: tbl_df/tbl/data.frame)
##  $ participant_id : num [1:87] 1 2 3 4 5 6 7 8 9 10 ..
##  $ vignette_type  : num [1:87] 1 1 1 1 1 1 1 1 1 1 ...
##  $ gender         : num [1:87] 1 2 1 2 1 1 1 2 1 1 ...
##  $ age            : num [1:87] 52 37 55 42 53 42 53 40
##  $ age_c          : num [1:87] 3 1 3 2 3 2 3 2 3 2 ...
##  $ region         : num [1:87] 8 1 1 9 8 8 11 1 11 15
##  $ job            : num [1:87] 2 4 4 4 2 4 9 4 4 4 ...
##  $ monthinc       : num [1:87] 5 3 6 2 6 4 3 2 7 8 ...
##  $ edu            : num [1:87] 6 5 5 4 5 4 5 5 5 5 ...
##  $ edu_m          : num [1:87] 1 3 1 2 2 2 1 2 3 3 ...
##  $ edu_f          : num [1:87] 1 3 1 3 3 2 3 3 3 5 ...
##  $ class          : num [1:87] 4 4 5 5 7 5 3 4 5 5 ...
##  $ rich           : num [1:87] 2 2 4 3 3 2 2 1 3 1 ...
##  $ hire           : num [1:87] 3 2 4 3 4 3 5 3 2 4 ...
##  $ colleg         : num [1:87] 3 2 4 3 3 2 5 1 3 4 ...
##  $ friend         : num [1:87] 3 2 4 3 4 2 5 1 3 4 ...
##  $ partner        : num [1:87] 3 3 3 3 4 2 4 1 3 4 ...
##  $ a_inc          : num [1:87] 3 3 4 4 3 5 5 4 5 6 ...
##  $ a_inc_m        : num [1:87] 5 3 5 4 4 4 5 1 5 4 ...
##  $ a_inc_f        : num [1:87] 6 5 5 4 4 6 5 7 5 7 ...
##  $ a_edu          : num [1:87] 5 5 5 3 5 5 5 5 5 6 ...
##  $ a_edu_m        : num [1:87] 5 3 5 3 4 3 5 5 5 5 ...
##  $ a_edu_f        : num [1:87] 5 5 5 3 4 4 5 5 5 5 ...
##  $ a_class        : num [1:87] 7 8 7 6 7 8 7 5 8 9 ...
##  $ a_rich         : num [1:87] 4 4 4 3 3 4 4 4 4 5 ...
##  $ close          : num [1:87] 3 2 3 3 3 3 4 1 4 3 ...
##  $ comp           : num [1:87] 3 3 4 3 4 3 4 3 4 4 ...
##  $ conf           : num [1:87] 4 5 4 3 3 4 5 4 4 5 ...
##  $ assert         : num [1:87] 4 3 5 3 4 3 5 3 4 5 ...
##  $ knowledge      : num [1:87] 3 3 4 3 3 3 4 3 4 5 ...
##  $ dilig          : num [1:87] 3 3 4 3 4 3 4 3 4 5 ...
```

```
##  $ warm           : num [1:87] 4 3 3 3 4 3 4 3 4 4 ...
##  $ topic_knowledge: num [1:87] 3 3 4 3 3 3 4 3 4 4 ...
##  $ honest         : num [1:87] 3 3 5 3 4 3 4 3 4 4 ...
##  $ optim          : num [1:87] 3 4 4 3 3 4 4 3 4 4 ...
##  $ esteem         : num [1:87] 3 5 4 3 4 4 5 3 4 3 ...
##  $ edu_dif        : num [1:87] 1 0 0 1 0 1 0 0 0 1 ...
##  $ edu_m_dif      : num [1:87] 4 0 4 1 2 1 4 3 2 2 ...
##  $ edu_f_dif      : num [1:87] 4 2 4 0 1 2 2 2 2 0 ...
##  $ class_dif      : num [1:87] 3 4 2 1 0 3 4 1 3 4 ...
##  $ rich_dif       : num [1:87] 2 2 0 0 0 2 2 3 1 4 ...
```

```r
# Data wrangling

data <- dataset %>%
  select(vignette_type, gender, age, edu, class, knowledge, topic_knowledge, a_inc, a_edu, a_class) %>%
  filter(age > 35) %>%
  mutate(across(c(vignette_type, gender), factor)) %>%
  mutate(vignette_type = case_when(
    vignette_type == "1" ~ "higher-class",
    vignette_type == "2" ~ "lower-class",
    TRUE ~ vignette_type  )) %>%
  mutate(gender = case_when(
    gender == "1" ~ "male",
    gender == "2" ~ "female",
    TRUE ~ gender  )) %>%
  mutate(across(c(vignette_type, gender), factor)) %>%
  mutate(evaluator_gender = gender, evaluator_age = age, evaluator_edu = edu,
         evaluator_class = class, infer_knowledge = knowledge, perceived_inc = a_inc, perceived_edu = a_edu
         perceived_class = a_class) %>%
  select(vignette_type, perceived_inc, perceived_edu, perceived_class, infer_knowledge, topic_knowledge, ev

# Export data
write_xlsx(data, "data.xlsx")
```

Evaluators read one of the two (higher-class and lower-class) vignettes of conversation and indicate their inferences of the listener.

perceived_( ) refers to evaluators' perception of the narrator. evaluator_( ) refers to evaluators' demographic info.

Analysis

Variable Description

1. Independent variable: Two vignettes with basic explanation levels

- 1 higher-class topic vignette + 1 lower-class topic vignette

2. Dependent variables

- Listener's knowledge rating (7-point Likert)
- Listener's social class rating (10-point Likert)
- Evaluator's knowledge of topic (10-point Likert)
- Evaluator's social class (7-point Likert)

Analysis Plan

A. Relationship between evaluator social class and knowledge (manipulation check)

- Analysis 1. Correlation analysis (within each vignette) & Independent samples t-test (between two social class groups of evaluators) to check (1) if the higher the social class is, the greater the knowledge of higher-class topic is and (2) if higher (lower) social class predicts knowledge of higher-class (lower-class) topic.
- Plots:
  - (1) Scatter plot + fitted line visualizing the relationship
  - (2) Histograms visualizing the data distribution
  - (3) Bar plots with the error bars where each bar represents the mean of a group
- Tables:
  - (1) Descriptive statistics of means & standard deviations
  - (2) Correlation matrix with correlation coefficients, significance levels
  - (3) Summary of t-test results

B. Compare social class ratings between two vignettes

- Analysis: Independent samples t-test (between two vignettes) to compare average social class ratings
- Plots:
  - (1) Histograms visualizing the data distribution
  - (2) Bar plots with the error bars where each bar represents the mean of a group
- Tables:
  - (1) Descriptive statistics of means & standard deviations
  - (2) Summary of t-test results

Result 1. Descriptive Statistics

```r
data <- read_xlsx("data.xlsx")

high_vignette <- data %>%
  filter(vignette_type=="higher-class")
low_vignette <- data %>%
  filter(vignette_type=="lower-class")

high_vignette %>%
  summarise(
    avg_evaluator_class = mean(evaluator_class, n
    sd_evaluator_class = sd(evaluator_class, na.r
    sd_topic_knowledge = sd(topic_knowledge, na.rm = TRUE),
    avg_perceived_class = mean(perceived_class, na.rm = TRUE),
    sd_perceived_class = sd(perceived_class, na.rm = TRUE))
```

```
## # A tibble: 1 x 5
##   avg_evaluator_class sd_evaluator_class sd_top
##                 <dbl>              <dbl>
## 1                4.73               1.48
## # i 1 more variable: sd_perceived_class <dbl>
```

```r
low_vignette %>%
  summarise(
    avg_evaluator_class = mean(evaluator_class, na
    sd_evaluator_class = sd(evaluator_class, na.rm
    sd_topic_knowledge = sd(topic_knowledge, na.rm
    avg_perceived_class = mean(perceived_class, na
    sd_perceived_class = sd(perceived_class, na.rm
```

```
## # A tibble: 1 x 5
##   avg_evaluator_class sd_evaluator_class sd_topic_knowledge avg_perceived_class
##                 <dbl>              <dbl>              <dbl>               <dbl>
## 1                5.03               1.73              0.806                4.83
## # i 1 more variable: sd_perceived_class <dbl>
```

Result 2. Correlation analysis of evaluator knowledge

Correlation Test, Scatter Plot, and Correlation Matrix

```r
cor.test(high_vignette$evaluator_class, high_vignette$topic_knowledge)
```

```
##
##  Pearson's product-moment correlation
##
## data:  high_vignette$evaluator_class and high_vignette$topic_knowledge
## t = 2.6167, df = 28, p-value = 0.01415
## alternative hypothesis: true correlation is not equal 
## 95 percent confidence interval:
##  0.09877405 0.69288712
## sample estimates:
##       cor
## 0.4432694
```

```r
ggplot(high_vignette, aes(x = evaluator_class, y = topic_
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", color = "skyblue3") +
  labs(title = "Relationship between evaluator class and 
       x = "Evaluator social class",
       y = "Knowledge of higher-class topic")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```


```r
cor_matrix_1 <- cor(high_vignette[c("evaluator_class", "t
print(cor_matrix_1)
```

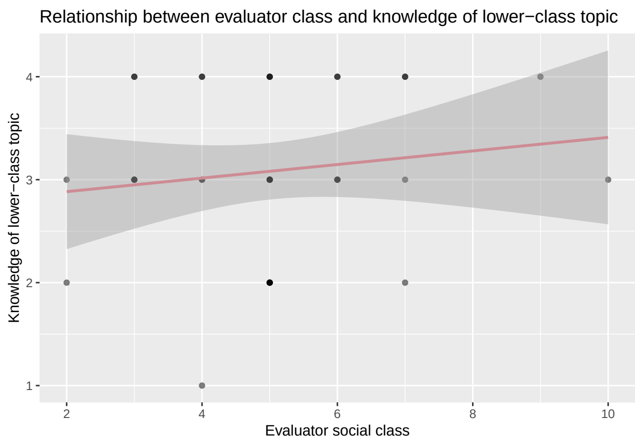
```
##                 evaluator_class topic_knowledge
## evaluator_class       1.0000000       0.4432694
## topic_knowledge       0.4432694       1.0000000
```

```r
cor.test(low_vignette$evaluator_class, low_vignette$topic_
```

```
##
##  Pearson's product-moment correlation
##
## data:  low_vignette$evaluator_class and low_vignette$t
## t = 0.83369, df = 34, p-value = 0.4103
## alternative hypothesis: true correlation is not equal 
## 95 percent confidence interval:
##  -0.1961186  0.4491853
## sample estimates:
##       cor
## 0.1415367
```

```
ggplot(low_vignette, aes(x = evaluator_class, y =
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", color = "lightpink3"
  labs(title = "Relationship between evaluator cl
       x = "Evaluator social class",
       y = "Knowledge of lower-class topic")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```




```
cor_matrix_2 <- cor(low_vignette[c("evaluator_cla
print(cor_matrix_2)
```

```
##                   evaluator_class topic_knowledge
## evaluator_class         1.0000000       0.1415367
## topic_knowledge         0.1415367       1.0000000
```

Result 3.1. Independent Samples T-test of evaluator knowledge

```
median_class <- median(high_vignette$evaluator_class, r
high_vignette$group <- ifelse(high_vignette$evaluator_c        _c        -class", "lower-class")

t_test_result <- t.test(topic_knowledge ~ group, data = high_vignette)
print(t_test_result)
```

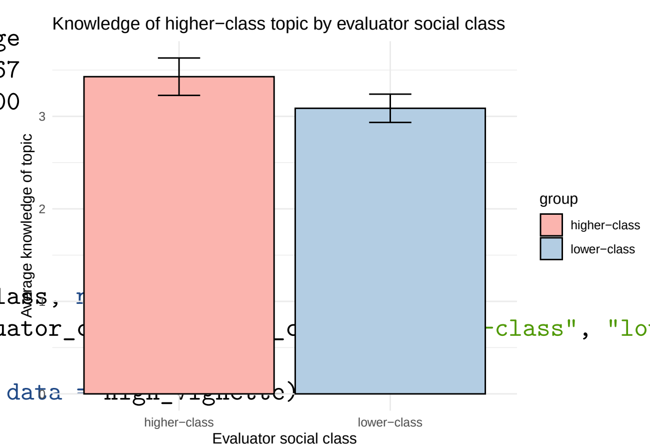
```
##
##  Welch Two Sample t-test
##
## data:  topic_knowledge by group
## t = 1.3484, df = 13.621, p-value = 0.1995
## alternative hypothesis: true difference in means between group higher-class and group lower-class is not
## 95 percent confidence interval:
##  -0.2031980  0.8864278
## sample estimates:
## mean in group higher-class  mean in group lower-class
##                   3.428571                   3.086957
```

```
group_summary <- high_vignette %>%
  group_by(group) %>%
  summarise(
    average_knowledge = mean(topic_knowledge, na.rm = TRU
    sem = sd(topic_knowledge, na.rm = TRUE) / sqrt(n())
  )
print(group_summary)
```

```
## # A tibble: 2 x 3
##   group        average_knowledge   sem
##   <chr>                    <dbl> <dbl>
## 1 higher-class              3.43 0.202
## 2 lower-class               3.09 0.153
```

Result 3.2. Bar plot of evaluator knowledge

```
ggplot(group_summary, aes(x = group, y = average_knowledg
  geom_bar(stat = "identity", position = position_dodge()
  geom_errorbar(aes(ymin = average_knowledge - sem, ymax =
                width = 0.2, position = position_dodge(0.
  labs(title = "Knowledge of higher-class topic by evalua
       x = "Evaluator social class", y = "Average knowled
  scale_fill_brewer(palette = "Pastel1") +
  theme_minimal()
```



Result 4.1 Independent Samples T-test of listener social class

```
t_test_result_2 <- t.test(infer_knowledge ~ vignette_type
print(t_test_result_2)
```

```
##
##  Welch Two Sample t-test
##
## data:  infer_knowledge by vignette_type
## t = 2.2241, df = 64, p-value = 0.02967
```

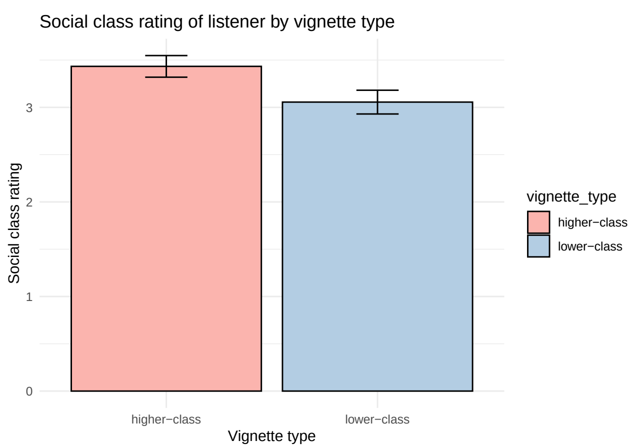
```
## alternative hypothesis: true difference in means between group higher-class and group lower-class is not
## 95 percent confidence interval:
##  0.03845784 0.71709771
## sample estimates:
## mean in group higher-class  mean in group lower-class
##                   3.433333                   3.055556
```

```r
group_summary_2 <- data %>%
  group_by(vignette_type) %>%
  summarise(
    average_infer_knowledge = mean(infer_knowledge, na.rm = TRUE),
    sem_infer = sd(infer_knowledge, na.rm = TRUE) / sqrt(n())
  )
print(group_summary_2)
```

```
## # A tibble: 2 x 3
##   vignette_type average_infer_knowledge sem_infer
##   <chr>                           <dbl>     <dbl>
## 1 higher-class                     3.43     0.114
## 2 lower-class                      3.06     0.126
```

Result 4.2. Bar plot of listener social class

```r
ggplot(group_summary_2, aes(x = vignette_type, y = average_infer_knowledge, fill = vignette_type)) +
  geom_bar(stat = "identity", position = position_dodge(), color = "black") +
  geom_errorbar(aes(ymin = average_infer_knowledge - sem_infer, ymax = average_infer_knowledge + sem_infer),
                width = 0.2, position = position_dodge(0.9)) +
  labs(title = "Social class rating of listener by vignette type",
       x = "Vignette type", y = "Social class rating") +
  scale_fill_brewer(palette = "Pastel1") +
  theme_minimal()
```



Discussion

The first port of this analysis explored the relationship between participants' social class and their knowledge of various conversation topics. The social class of individuals (data) was measured on a 10-point likert scale (MacArthur Subjective SES ladder), and their knowledge across different topics (that are typically well-known by either higher or lower social class groups) was assessed on a 7-point likert scale.

The analyses reveals an average participant social class of r mean(dataset$participant_social_class, na.rm = TRUE), with a standard deviation of r sd(dataset$participant_social_class, na.rm = TRUE). Knowledge on the topics shows an average score of r mean(dataset$topic_knowledge, na.rm = TRUE) and a standard deviation of r sd(dataset$topic_knowledge, na.rm = TRUE).

The correlation test indicates a significant relationship between social class and knowledge, with a correlation coefficient of r cor_test_result$estimate and a p-value of r cor_test_result$p.value. This suggests that as participants' social class increases, their knowledge on higher-class common ground topics will also tend to increase, and vice versa.

A scatter plot visualizes this relationship with a fitted line indicating the direction and strength of the relationships. The correlation matrix additionally reveals a coefficient of r cor_matrix["participant_social_class", "topic_knowledge"].

The findings ultimately suggest that socioeconomic factors indeed play a role in shaping individuals' cultivated knowledge of specific experiences or fields.

Discussion

As Fiske & Markus (2012) note, social class profoundly impacts social identity, as it often dictates the social circles one interacts with and the societal norms one adheres to. The distinct life circumstances and standards build rigorous common ground within social class groups. Each norm, experience, and cultural reference builds unique knowledge bases (Lareau, 2014) and physical, psychological, and behavioral propensities (Kraus et al., 2012; Manstead, 2018; Piff et al., 2017).

Notably, in settings where diverse social identities interact, bridging these common grounds will be necessary for productive conversation. This would involve being aware of each other's social class background, predicting gaps in perspectives and knowledge, and explaining concepts as occasion demands (Allen, 2020). It is well known that speakers' language production reveals much about their awareness of the listener's knowledge. This study takes an additional step by illustrating how the very act of establishing new common ground also reveals the listener's social class. Considering that people from different social classes have access to different information, the listener design will enable inferences about social class.

By probing whether the speaker's words hint at the social class background of the listener, this study introduces one subtle and intricate way in which class information circulates during social interactions. This study also points out the broader societal consequences of status perception. Cuddy and colleagues (2008) showed that subtle social status cues can respectively predict impressions—for example, warmth and competence (i.e., Stereotype Content Model (SCM); (Durante et al., 2017)—which could influence interpersonal relationships and selection processes (Kraus et al., 2017; Rivera & Tilcsik, 2016; Stangor, 2016). In a large sense, unraveling the dynamics of social class signaling can yield meaningful insight into the barriers that may account for socioeconomic mobility.

References

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Durante, F., Tablante, C. B., & Fiske, S. T. (2017). Poor but warm, rich but cold (and Competent): Social classes in the stereotype content model. *Journal of Social Issues*, *73*(1), 138–157.

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