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## Log-linear Modeling

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## Overview

> Our project
> Log-linear modeling
> Log-linear modeling in the field
> Summary
> References

## Our project

> The difference between size reading and gradable readig:

- That sure is a big ship. (size reading)
. He sure is a big idiot. (gradable reading)
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## Our project

> Lassy corpus
> Adjective+noun pairs
> Three adjectives:

- Reusachtig
- Gigantisch
. Kolossaal
> Three other variables
. Position in sentence (e.g.: subject, object)
- Determiner (definite/indefinite)
- Gradable/size reading
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## Our project

> Do these variables play a role in the choice between on of the the three adjectives?
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## Log-linear modeling

> A way of modeling the cell count of contingecy tables with categorical data (like Chi-square).
> No distinction between dependent and independent variables.
> Assumes Poisson-distributed data (like data obtained from a corpus).

## Log-linear modeling

> Remember Chi-Square?

- $\mathrm{F}^{\mathrm{e}}=$ (row total x column total) / total

|  | Y Yes | No | total |
| :---: | :---: | :---: | :---: |
| $\begin{aligned} & \text { X } \\ & \text { Yes } \end{aligned}$ | $\begin{array}{\|l\|} \hline 20 \\ (37,5) \\ \hline \end{array}$ | $\begin{aligned} & 40 \\ & (22,5) \end{aligned}$ | 60 |
| No | $\begin{array}{\|l\|} \hline 130 \\ (112,5) \\ \hline \end{array}$ | $\begin{aligned} & 50 \\ & (67,5) \end{aligned}$ | 180 |
| total | 150 | 90 | 240 |

## Log-linear modeling

$>\mathrm{F}^{\mathrm{e}}=($ row total $\times$ column total $) /$ total
$>F_{i j}{ }^{e}=\left(F_{i .}{ }^{0} \times F_{. j}{ }^{0}\right) / N$
> Log-linear modeling uses the natural logarithm (In) to transform the data. When using In, the following rules apply:

- $\ln (a \times b)=\ln a+\ln b$
- $\ln (a / b)=\ln a-\ln b$ groningen


## Log-linear modeling

$>F_{i j}{ }^{e}=\left(F_{i .}{ }^{0} \times F_{. j}{ }^{0}\right) / N$
$>\ln \mathrm{F}_{\mathrm{ij}}{ }^{\mathrm{e}}=\ln \mathrm{F}_{\mathrm{i} .}{ }^{0}+\ln \mathrm{F}_{. j}{ }^{0}-\ln \mathrm{N}$
> "the terms which were originally multiplied are replaced by a linear combination of logarithmic terms: a log-linear model" (Rietveld \& van Hout: 1993)
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## Log-linear modeling

$$
\begin{aligned}
>F_{i j}{ }^{e} & =\left(F_{i .}{ }^{0} \times F_{. j}{ }^{\circ}\right) / N \\
& =(150 \times 180) / 240 \\
& =112,5
\end{aligned}
$$

$>\ln F_{i j}{ }^{e}=\ln F_{i .}{ }^{0}+\ln F_{. j}{ }^{0}-\ln N$

|  | Y <br> Yes | No | total |
| :--- | :--- | :--- | :--- |
| X <br> Yes | 20 <br> $(37,5)$ | 40 <br> $(22,5)$ | 60 |
| No | $\mathbf{1 3 0}$ <br> $\mathbf{( 1 1 2 , 5 )}$ | 50 <br> $(67,5)$ | $\mathbf{1 8 0}$ |
| total | $\mathbf{1 5 0}$ | 90 | $\mathbf{2 4 0}$ |

$=\ln 150+\ln 180-\ln 240$

$$
=5.193+5.011-5.481=4.723
$$

$$
\mathrm{F}_{\mathrm{ij}} \mathrm{e}^{e}=e^{4.723} \text { (ANTILOG) }
$$

$$
=112.5
$$

## Log-linear modeling

> Having transformed the data, you can now think of the contingency table as reflecting various main effects and interacting effects that are added together in a linear fashion to create the observed table of frequencies.
$>\operatorname{Ln} F_{i j}{ }^{\mathrm{e}}=\mu+\lambda_{\mathrm{i}}^{\mathrm{A}}+\lambda_{\mathrm{j}}^{\mathrm{B}}+\lambda_{\mathrm{jj}} \mathrm{AB}^{\mathrm{AB}}$

- $\mu=$ overall mean of the natural log of the expected frequencies
- $\lambda=$ represents an "effect" that the variable(s) has(/have) on the cell frequencies
- $A \& B=$ the variables
- i\&j = categories within the variables (rows \& columns)
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## Log-linear modeling

$>\operatorname{Ln} F_{i j}{ }^{\mathrm{e}}=\mu+\lambda_{\mathrm{i}}^{\mathrm{A}}+\lambda_{\mathrm{j}}^{\mathrm{B}}+\lambda_{\mathrm{jj}} \mathrm{AB}^{\mathrm{AB}}$

- $\mu=$ overall mean of the natural log of the expected frequencies
. $\lambda=$ represents an "effect" that the variable(s) has(/have) on the cell frequencies
- $\mathrm{A} \& \mathrm{~B}=$ the variables
- $i \& j=$ categories within the variables (rows $\&$ columns)
- $\lambda_{i}^{A}=$ main effect for variable $A$
- $\lambda_{j}^{B}=$ main effect for variable $B$
- $\lambda_{\mathrm{jj}} \mathrm{AB}^{\mathrm{AB}}=$ interaction effect for variables $\mathrm{A} \& \mathrm{~B}$
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## Log-linear modeling

> Remember:

- Log-linear modeling is a way of modeling the cell count of contingecy tables with categorical data.
$>\operatorname{Ln} F_{i j}{ }^{\mathrm{e}}=\mu+\lambda_{\mathrm{i}}^{\mathrm{A}}+\lambda_{\mathrm{j}}^{\mathrm{B}}+\lambda_{\mathrm{jj}}^{\mathrm{AB}}$
. Is called the "saturated model".
- It has as many effects as the contingency table has cells.
- Therefore it has no degrees of freedom
- So it fits the data perfectly ( $\mathrm{F}^{\mathrm{e}}=\mathrm{F}^{\circ}$ )
- But the data is a sample (=/= population), so the model overfits the data.


## Log-linear modeling

> Fortunately the effects are combined additively, so it is easy to remove an effect and test if the model still fits the data.

- This is called the Model Selecting Log-linear Analysis.
- The goal is to find the most parsimonious ( $\approx$ simple) model that does not differ significantly from the saturated model (and thus from the observed frequencies).


## Log-linear modeling

> Model Selecting Log-linear Analysis.

- Is mostly done hierarchicaly:
- $\quad \lambda_{j j}{ }^{A B}$ is made up out of $\lambda_{i}^{A}$ and $\lambda_{j}{ }^{B}$, therefore $\lambda_{i}{ }^{A}$ and $\lambda_{j}{ }^{B}$ must be in the model when $\lambda_{j j}{ }^{A B}$ is.

|  | Backward deletion | $X^{2=}$ |
| :--- | :--- | :--- |
| 1. | $\operatorname{Ln} F_{i j}{ }^{\mathrm{e}}=\mu+\lambda_{\mathrm{i}}^{\mathrm{A}}+\lambda_{\mathrm{j}}^{\mathrm{B}}+\lambda_{\mathrm{jj}}{ }^{\mathrm{AB}}$ | 0 |
| 2. | $\operatorname{Ln~}_{\mathrm{ij}}{ }^{\mathrm{e}}=\mu+\lambda_{\mathrm{i}}^{\mathrm{A}}+\lambda_{\mathrm{j}}^{\mathrm{B}}$ | $?$ |
| 3. | $\operatorname{Ln~}_{\mathrm{i}}{ }^{\mathrm{e}}=\mu+\lambda_{\mathrm{i}}^{\mathrm{A}}$ | $?$ |
| 4. | $\operatorname{Ln} \mathrm{~F}_{\mathrm{ij}}{ }^{\mathrm{e}}=\mu$ | $?$ |

## Log-linear modeling

> This may not be the best approach for a $2 \times 2$ contingency table, but it is a very easy statistic for analyzing tables with more dimensions.

- For instance a $3 \times 3$ contingency table
$-\underset{\lambda_{j j k}}{\operatorname{LnCC}} \mathrm{~F}_{i j}^{\mathrm{e}}=\mu+\lambda_{\mathrm{i}}^{\mathrm{A}}+\lambda_{j}^{\mathrm{B}}+\lambda_{k}^{\mathrm{C}}+\lambda_{\mathrm{jj}}^{\mathrm{AB}}+\lambda_{j k} \mathrm{AC}+\lambda_{j k} \mathrm{BC}+$
- Extra dimensions (variables) leed to a large increase in main and higherorder (=interactional) effects and with log-linear modeling you can easily find out which effects help create the observed frequencies and which can be left out of the model.


## Log-linear modeling in the field

> De Haan \& van Hout - Statistics and Corpus Analysis: A Loglinear Analysis of Syntactic Constraints on Postmodifying Clauses (1986).
> Bell, Dirks, Levitt \& Dubno - Log-Linear Modeling of Consonant Confusion Data (1986).
> Girard \& Larmouth - Log-Linear Statistical Models: Explaining the Dynamics of Dialect Diffusion (1988).

## Summary

> Log-linear modeling
. Is a way of modeling the cell count of contingecy tables with categorical data.

- Replaces originally multiplied terms by a linear combination of logarithmic terms.
- Tries to find the most parsimonious model that does not differ significantly from the saturated model.


## References

> Toni Rietveld and Roeland van Hout (1993) Statistical Techniques for the Study of Language and Language Behavior. Mouton De Gruyter: Berlin.
> Alan Agresti (1996) An Introduction to Categorical Data Analysis. Wiley: New York.
> Ronald Christensen (1997) Log-Linear Models and Logistic Regression. Springer-Verlag: New York.

