# Simulating bilingual aphasia rehabilitation: Evidence from a computational model

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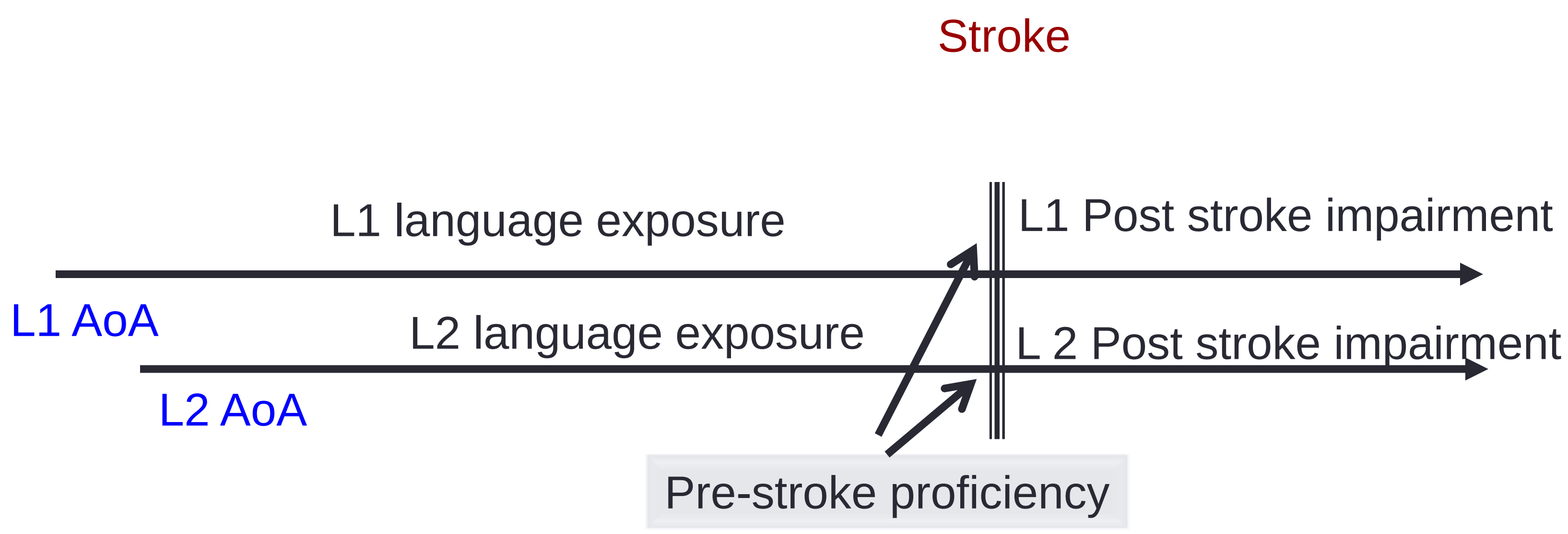
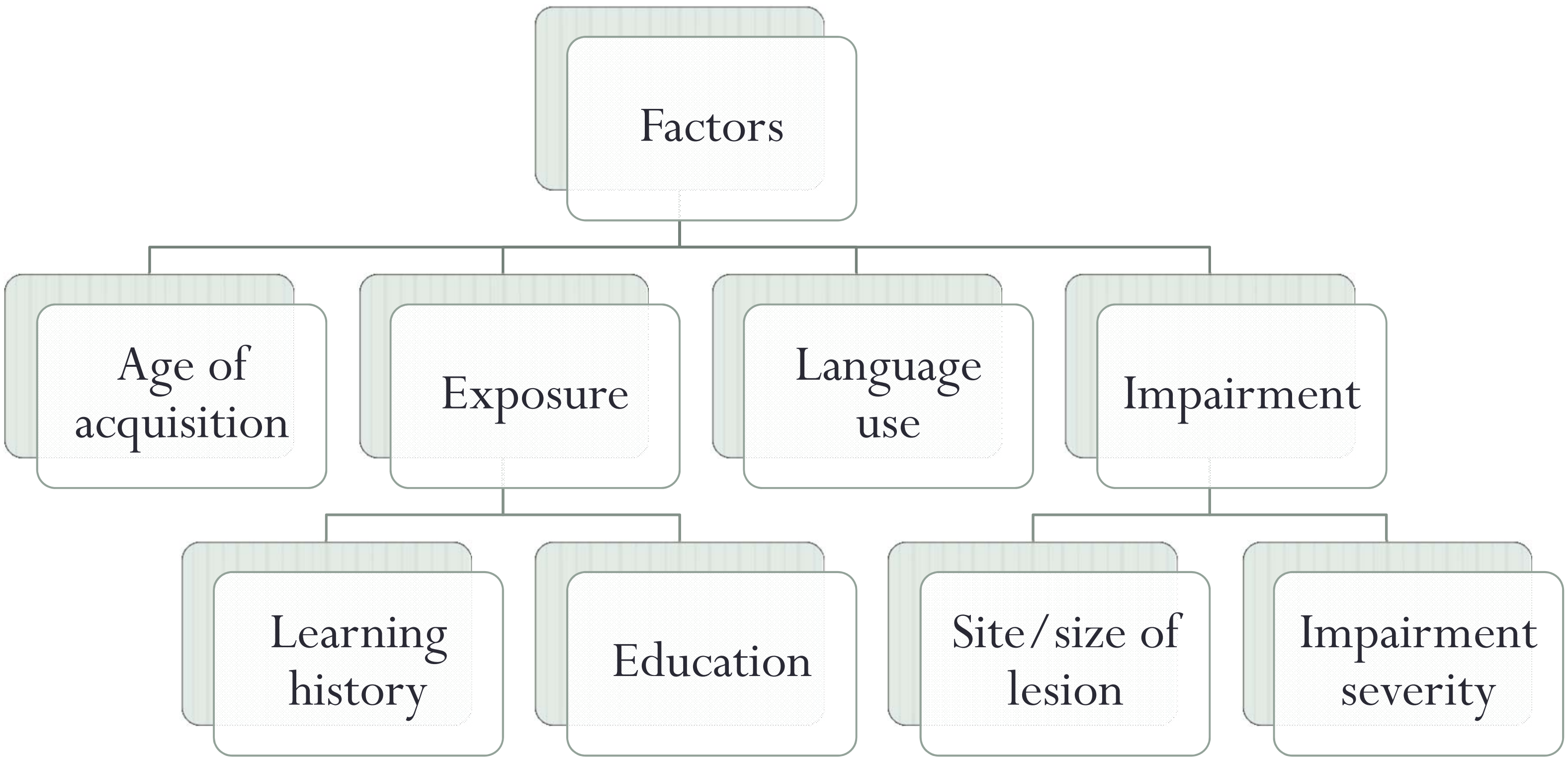
# Bilingual Aphasia



# Factors influencing language recovery and rehabilitation




Hernandez & Li, 2007; Li, Zhao, & McWhinney, 2007; Abutalebi, 2008

Fabbro, 2001a; Lorenzen & Murray, 2009; Mechelli, Crinion, et al., 2004

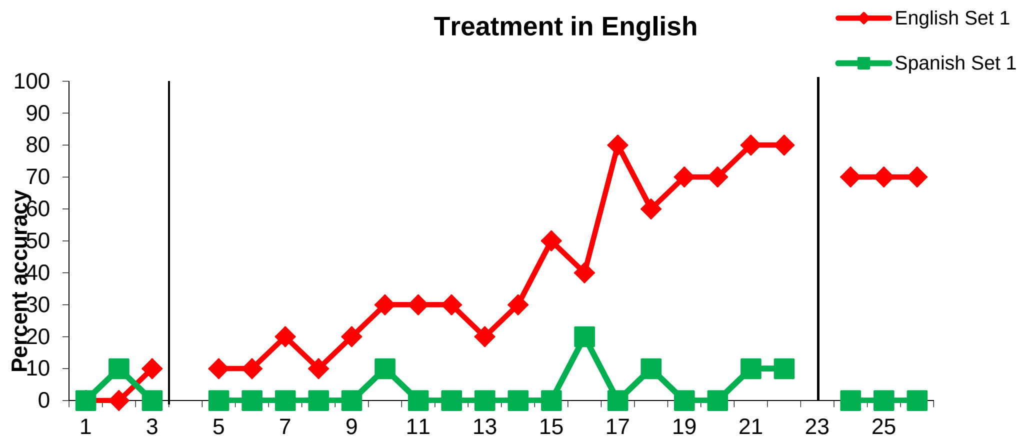
# Bilingual Aphasia Rehabilitation

- No consistent results on rehabilitation of bilingual aphasia (Lorenzen & Murray, 2008; Faroqi-Shah et al., 2010)

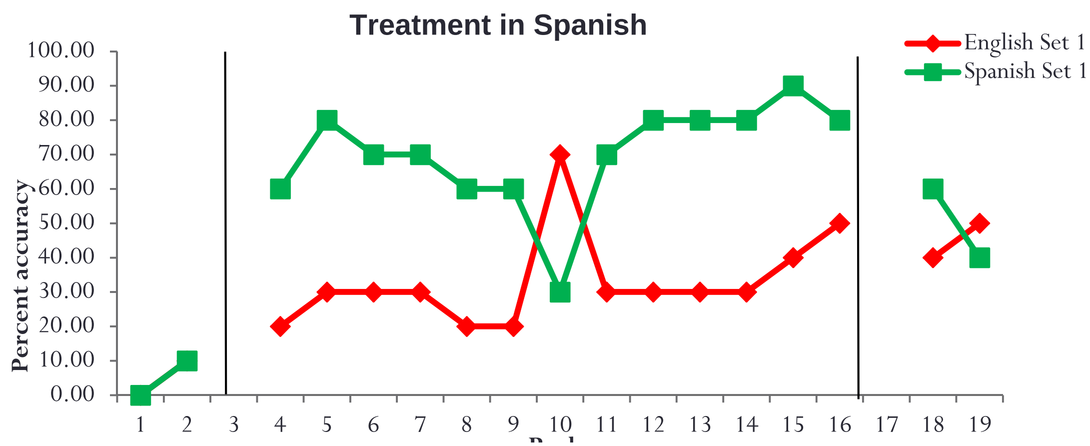
- Few systematic studies that have examined and observed the extent of cross language transfer but results vary

  (Croft et al., 2011; Edmonds & Kiran, 2006; Miertsch et al., 2009, Kiran & Roberts, 2009)

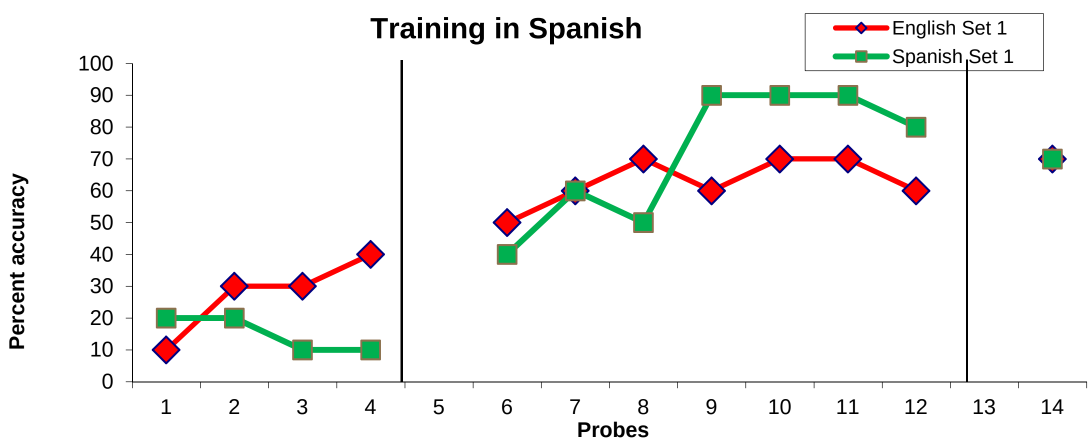
- For instance…




English dominant patient
Trained in English

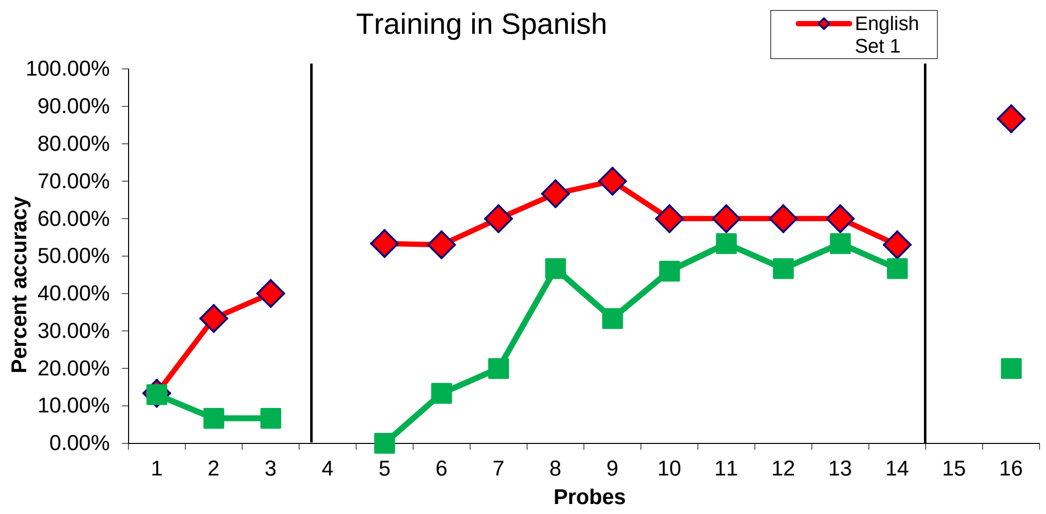



Equally proficient patient
Trained in Spanish

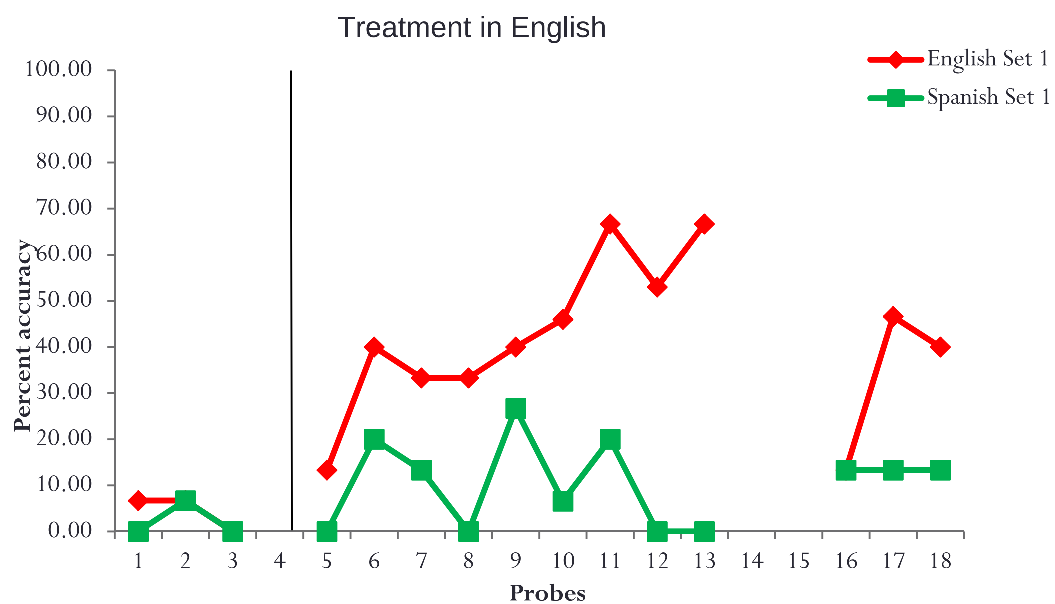



English dominant patient
Trained in Spanish

Edmonds & Kiran, 2006




English dominant patient
More impaired in Spanish
Trained in Spanish




Equally proficient
Trained in English

Kiran & Roberts, 2009

# Goal of this project

- Develop a computational simulation of bilingual aphasic naming deficits and rehabilitation of bilingual aphasia.
  - Similar to predicting rehabilitation of naming deficits (Plaut, 1996)

- Self Organizing Maps (Kohonen, 1995) is an type of artificial neural network that is based on unsupervised learning.

- SOMs operate in two modes
  - Training -builds the map using input examples
  - Mapping- classifies a new input vector

- SOMs have been used to understand bilingual language learning (Li, Zhao & McWhinney, 2007) and biological/psychiatric conditions (Hamalainen,1994; Hoffman, Grasemann, & Miikkulainen, 2011)

# Develop a computational simulation of bilingual aphasic naming deficits and rehabilitation of bilingual aphasia.

**Step 1**

- Model pre-stroke/normal bilingual language performance
  - Use AoA and exposure as training parameters
  - DISLEX should be able to match pre-stroke English and Spanish performance

**Step 2**

- Simulate damage to the lexicon
  - Distort associative connections with noise
  - DISLEX should be able to model impairment in patients

**Step 3**

- Use the model to predict treatment outcomes
  - Examine improvements in trained language and cross language transfer

## Step 1

- Model pre-stroke/normal bilingual language performance
  - Use AoA and exposure as training parameters
  - DISLEX should be able to match pre-stroke English and Spanish performance

# Input Data

300 words, including those used for treatment

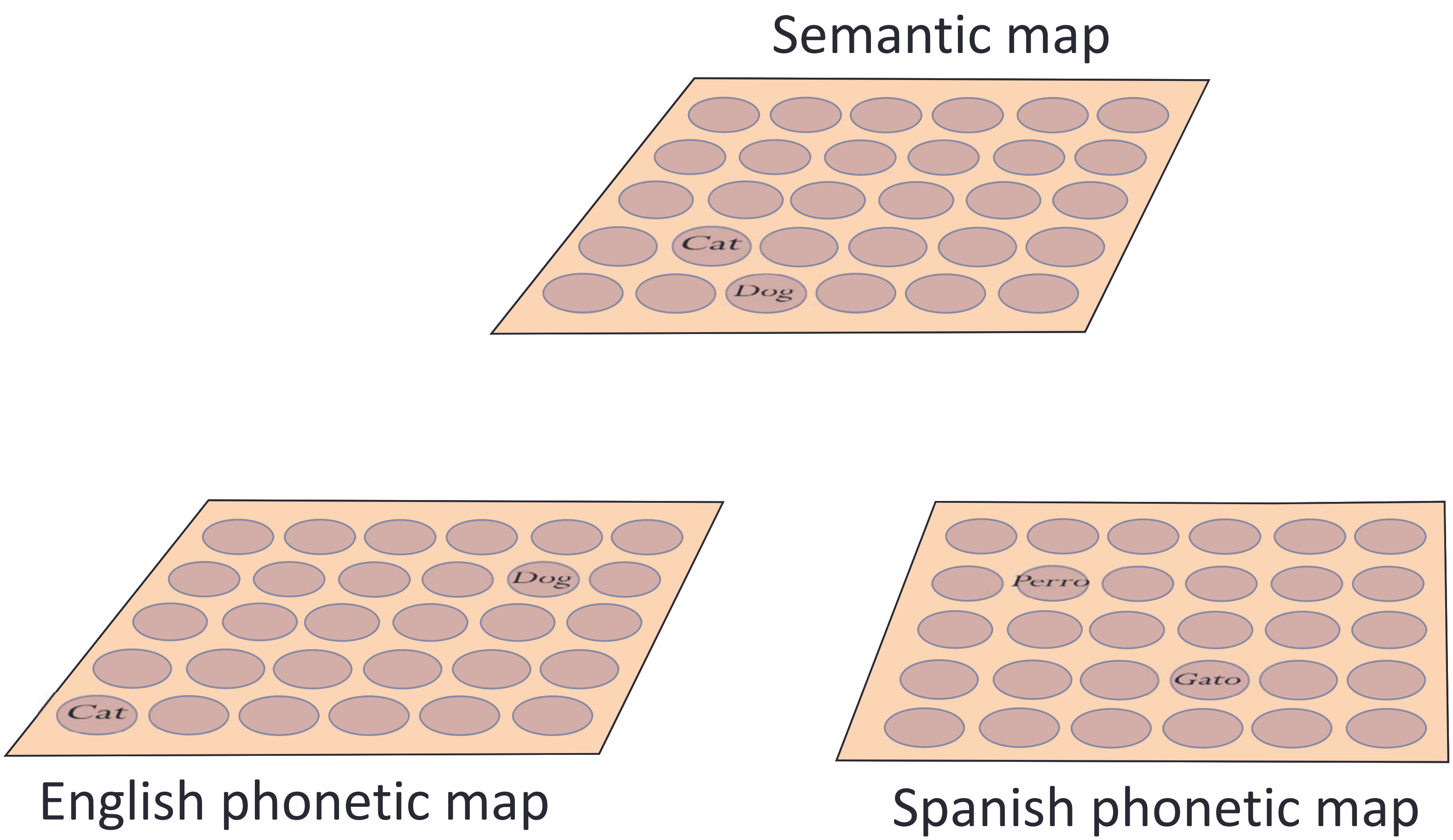
## Semantic representations

- 260 hand-coded binary features
- E.g. “can fly”, “is a container”, “can be used as a weapon”

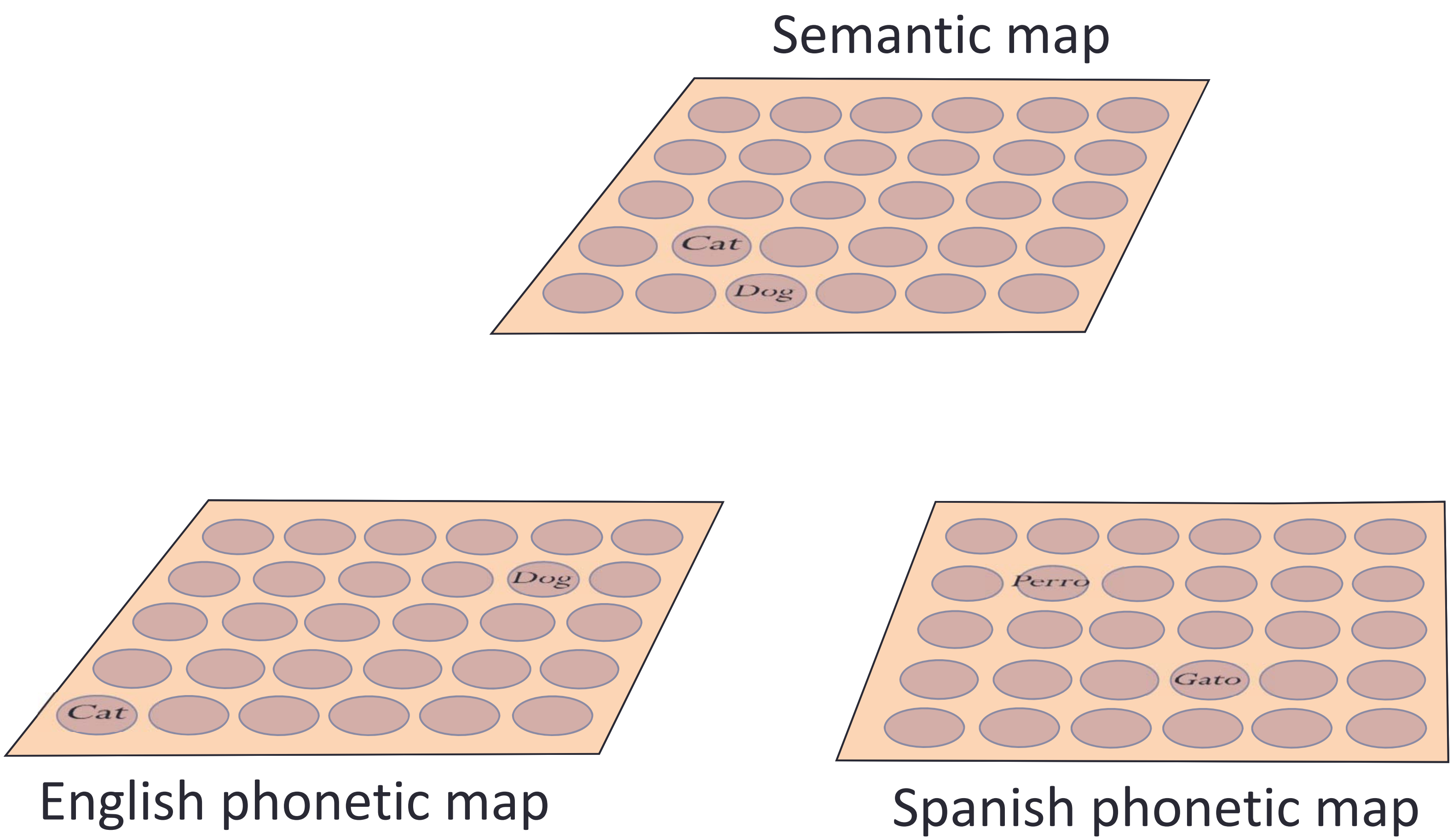
## Phonetic representations

- Based on English and Spanish IPA transcriptions
- Numerical representations of phonemes
- E.g. frontness, openness, roundedness for vowels

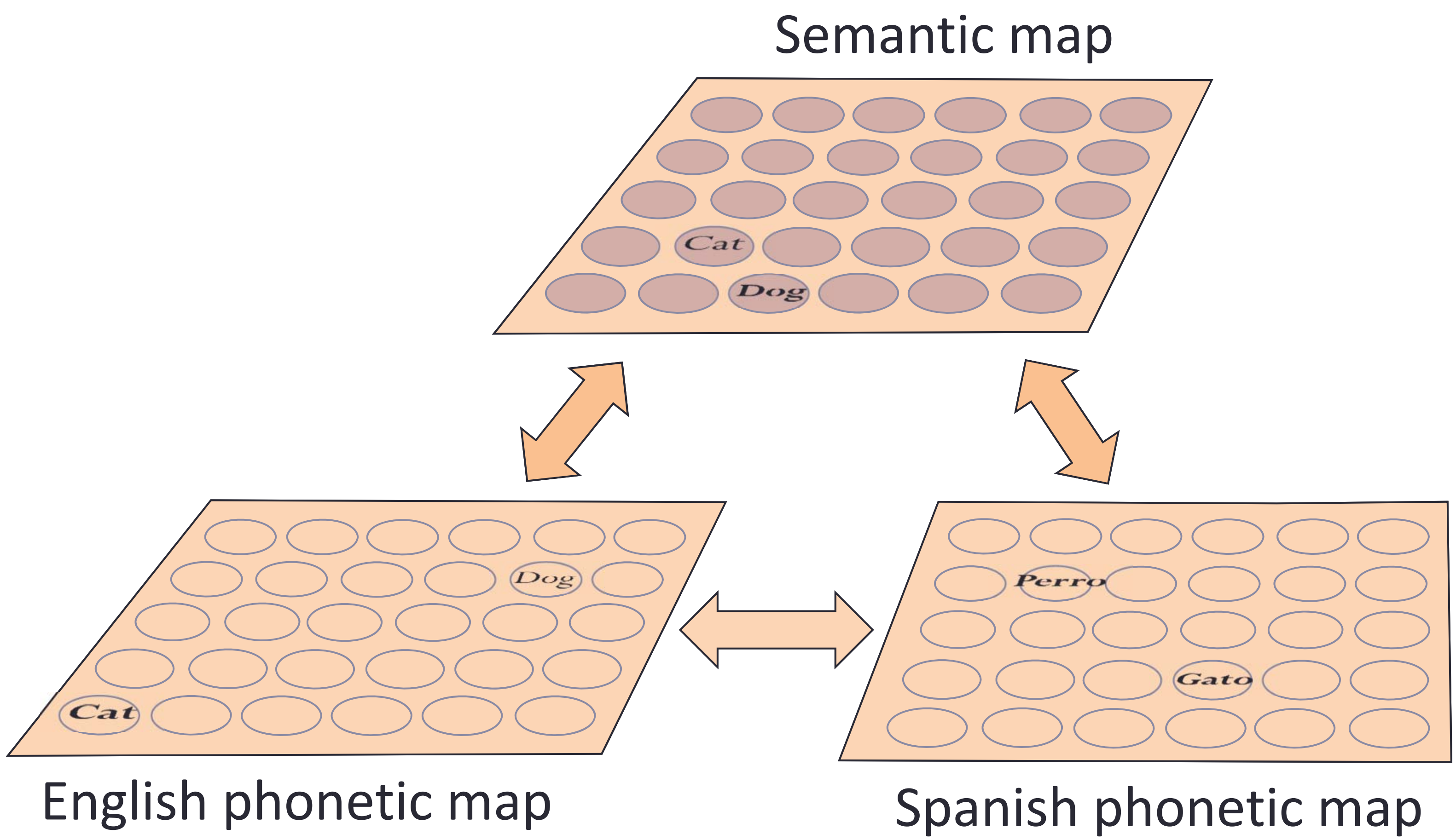
# The Bilingual DISLEX Model



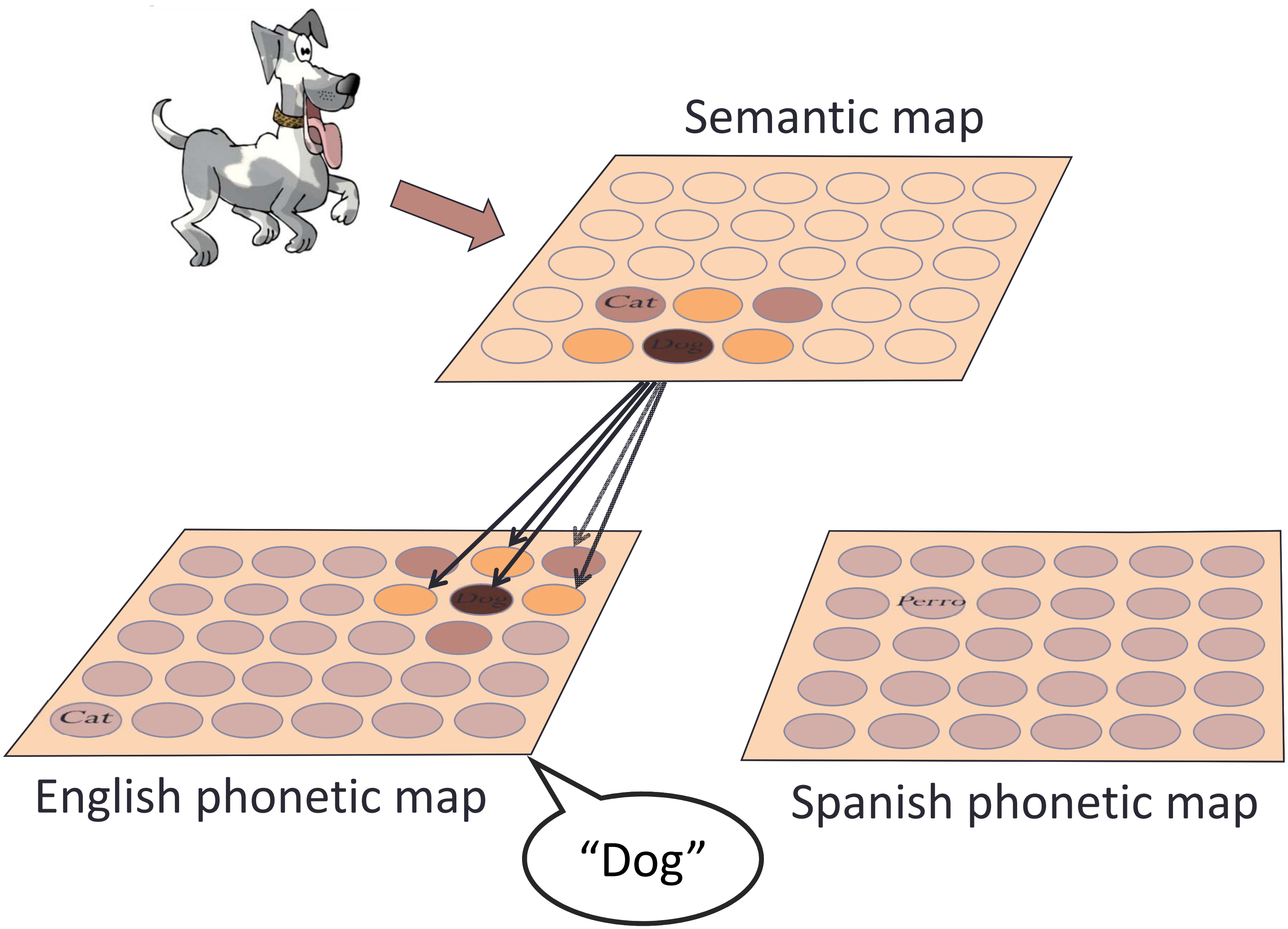
# The Bilingual DISLEX Model



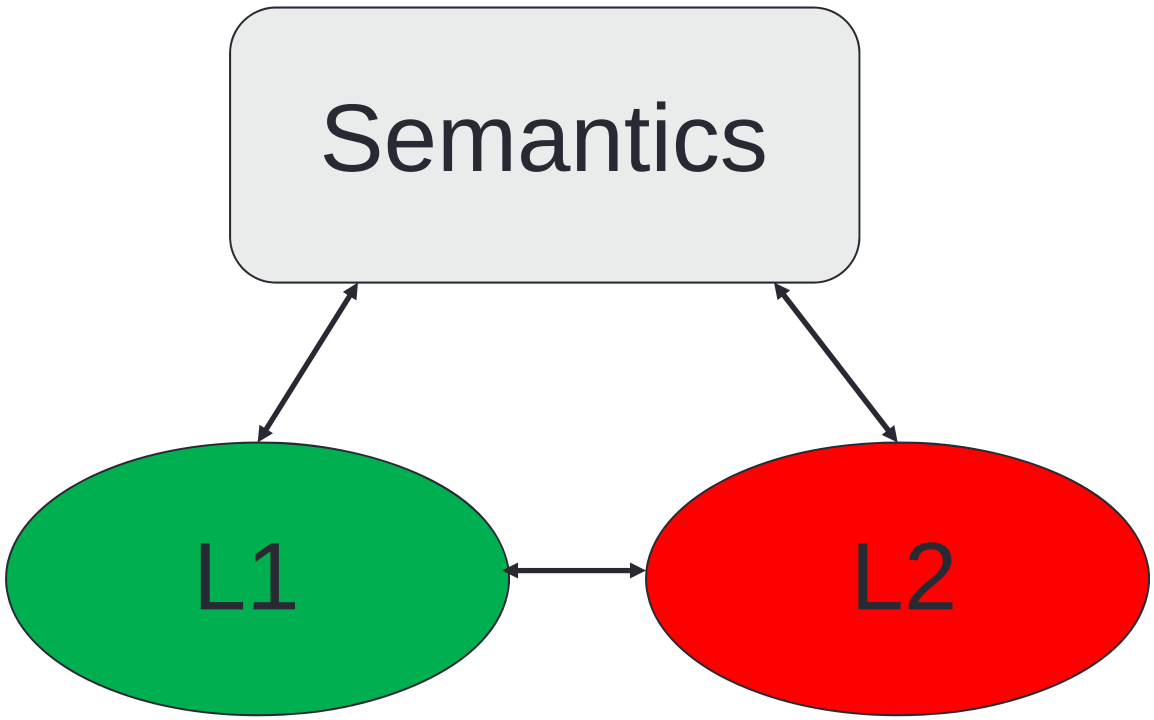
# The Bilingual DISLEX Model



# Naming Task


Semantic map
Cat
Dog
Cat
Dog
Perro
English phonetic map
"Dog"
Spanish phonetic map

# Model of Bilingual Lexical Access

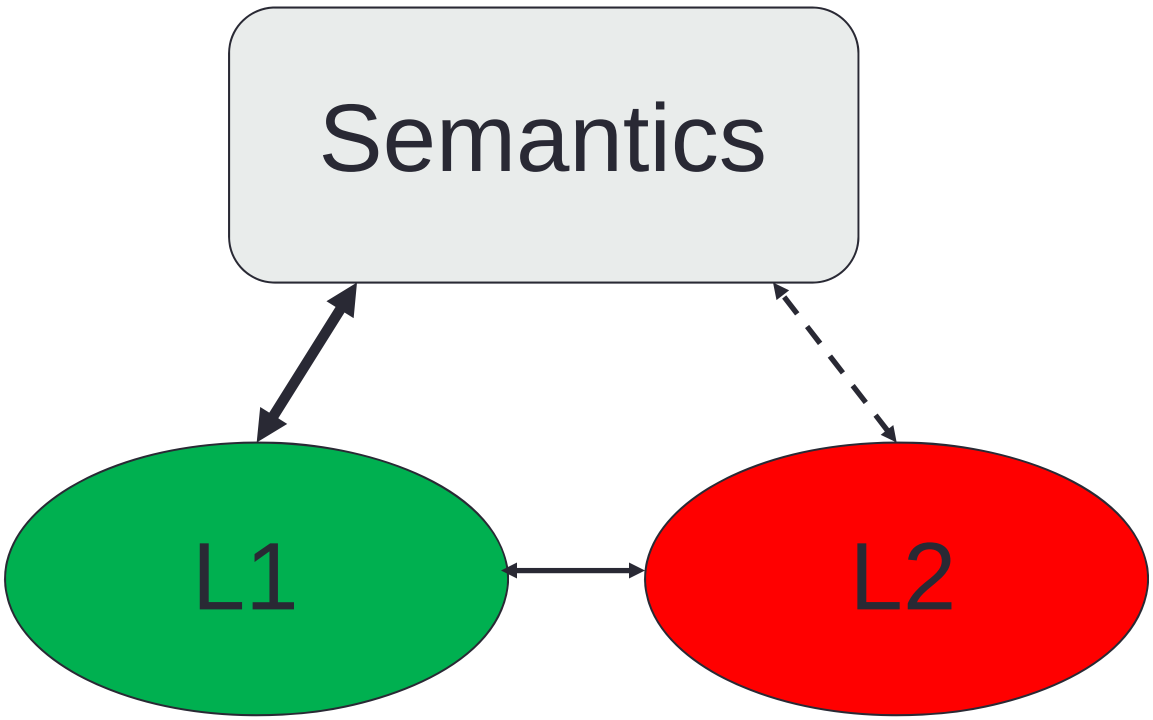



(de Groot, 1992, 1994)

Asymmetrical Model
(Kroll & Stewart, 1994

Kroll et al., 2010)

# Model of Bilingual Lexical Access




(de Groot, 1992, 1994)

Asymmetrical Model
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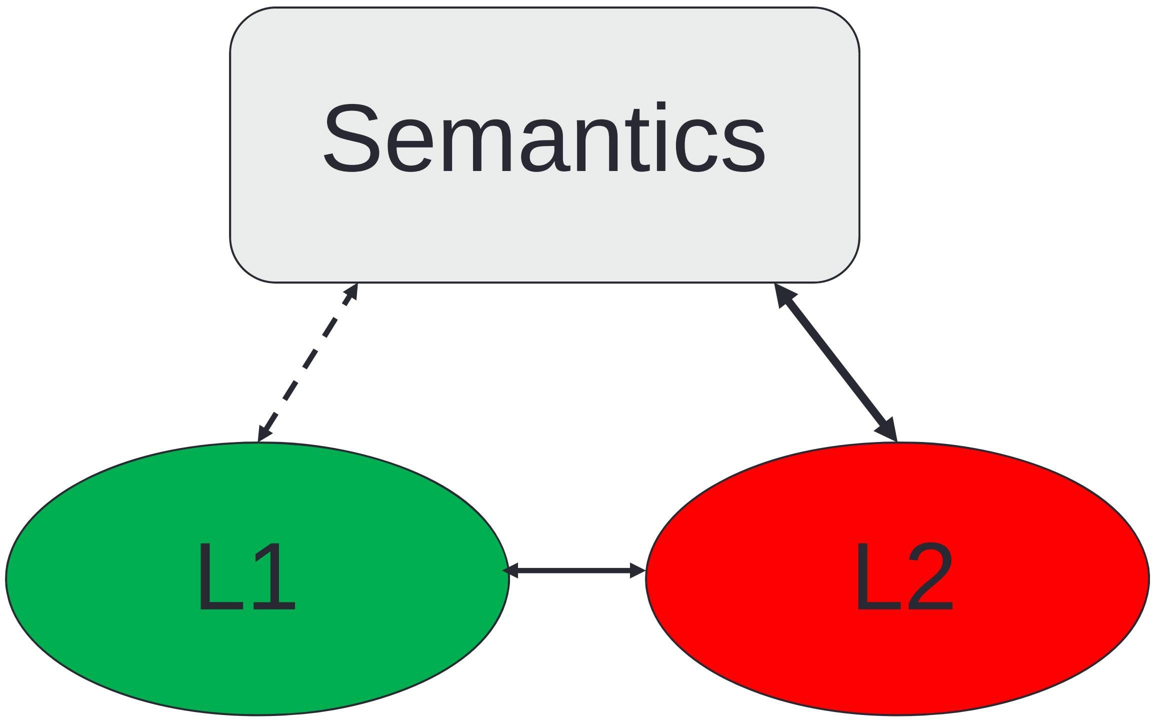
Kroll et al., 2010)

# Model of Bilingual Lexical Access




(de Groot, 1992, 1994)

Asymmetrical Model
(Kroll & Stewart, 1994

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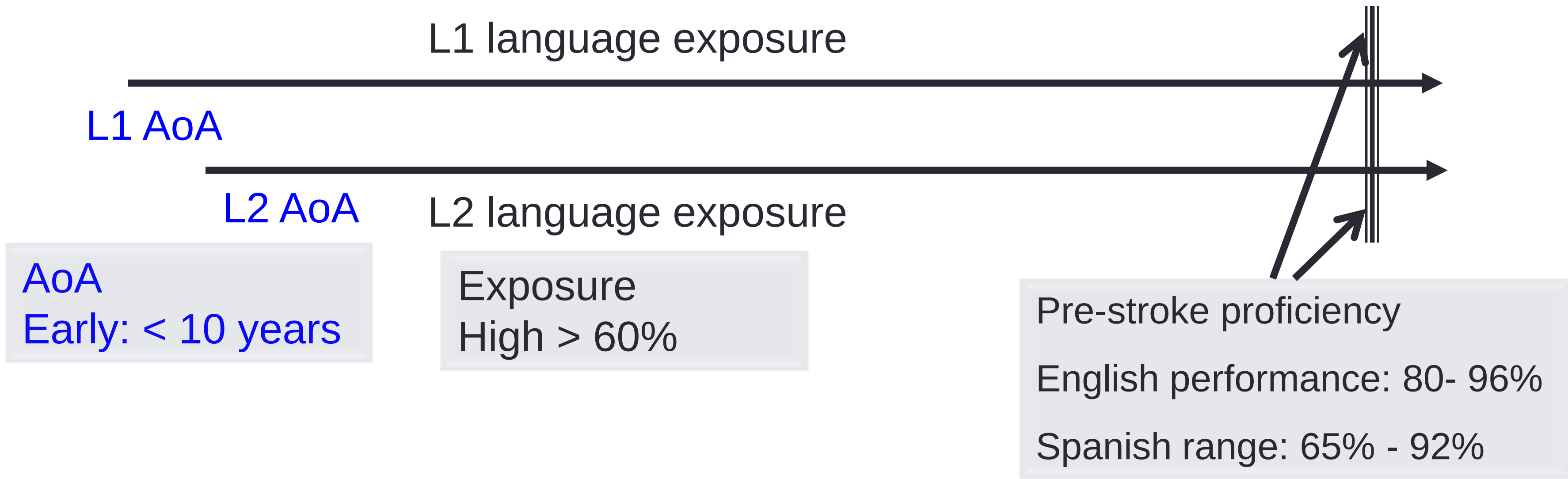
# Approach

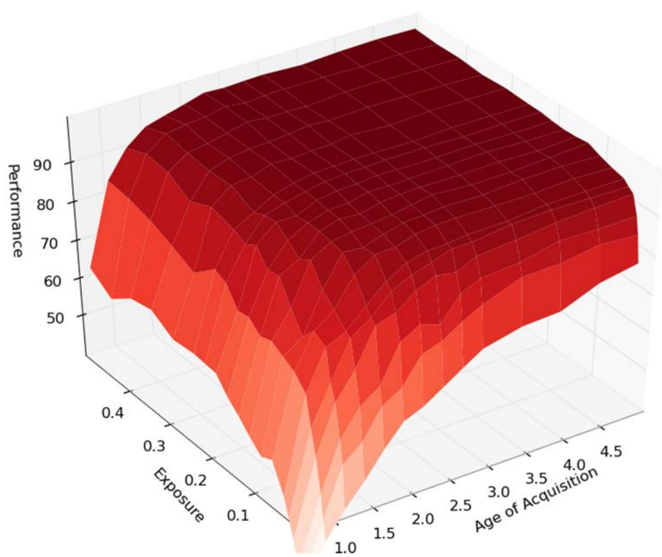



Information about AoA, Language exposure, proficiency obtained from a language use question – Kiran et al.( 2010, submitted)

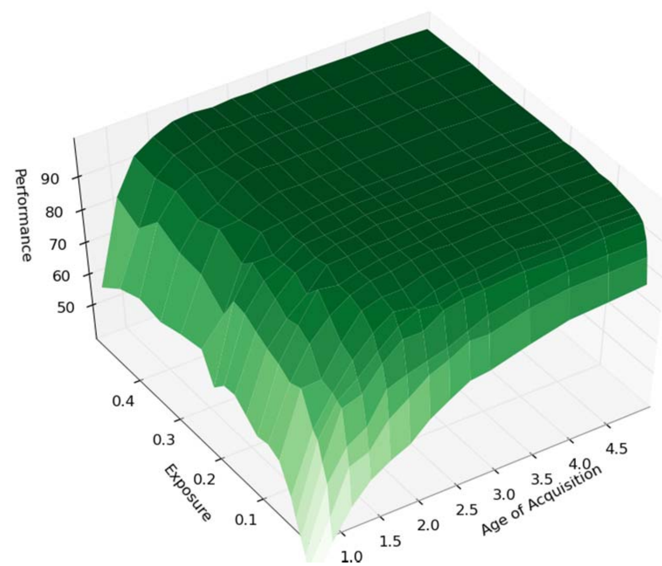
Simulate normal bilingual performance

- 39 normal bilinguals
- 19 patients with bilingual aphasia

(Grasemann et al., 2010; Grasemann et al., 2011; Kiran et al., 2010)

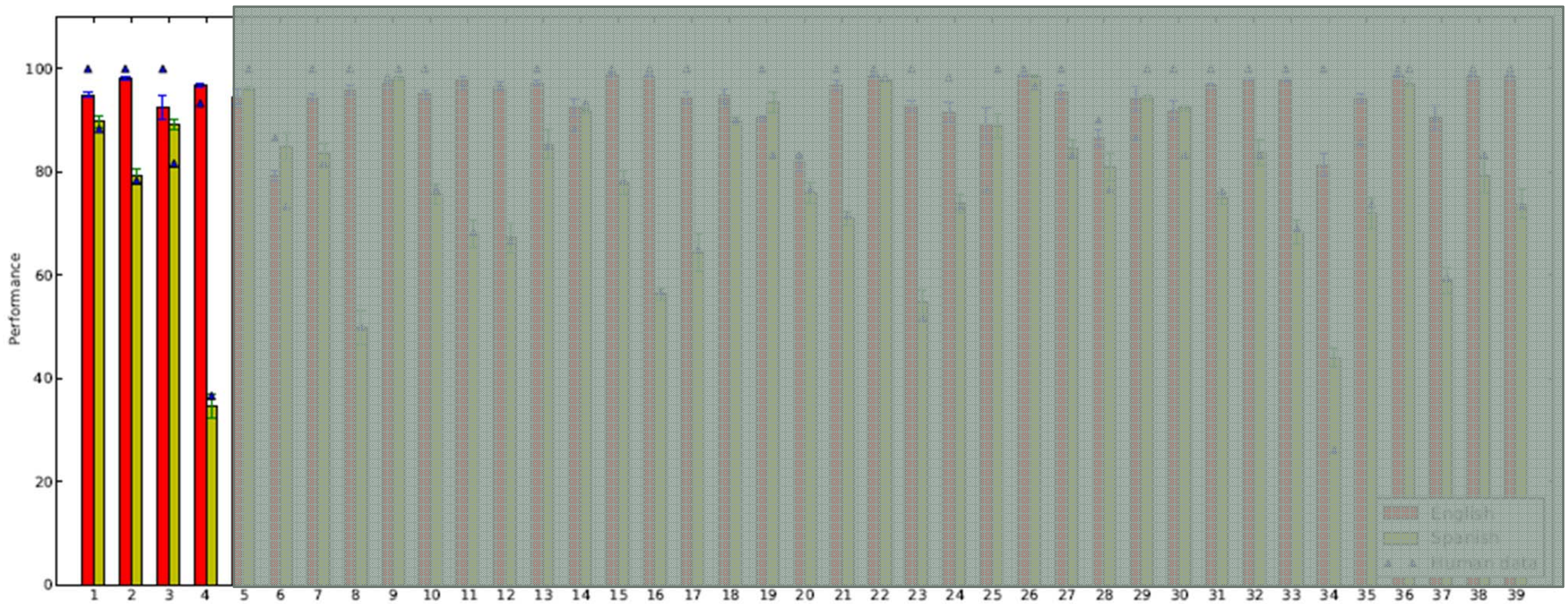



English




Spanish

# Results of simulation of normal bilingual individuals



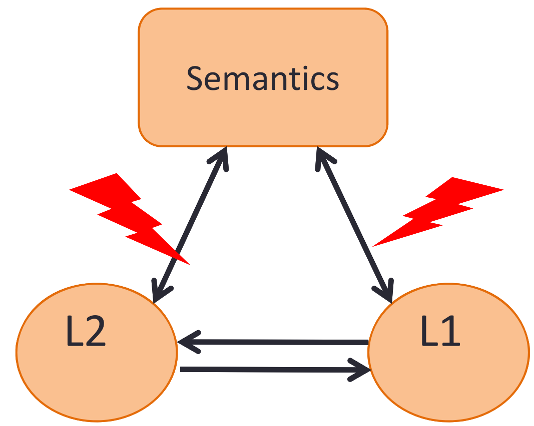

(Grasemann et al., 2010; Grasemann et al., 2011; Kiran et al., 2010)

## Step 2

- Simulate damage to the lexicon
  - Distort associative connections with noise
  - DISLEX should be able to model impairment in patients

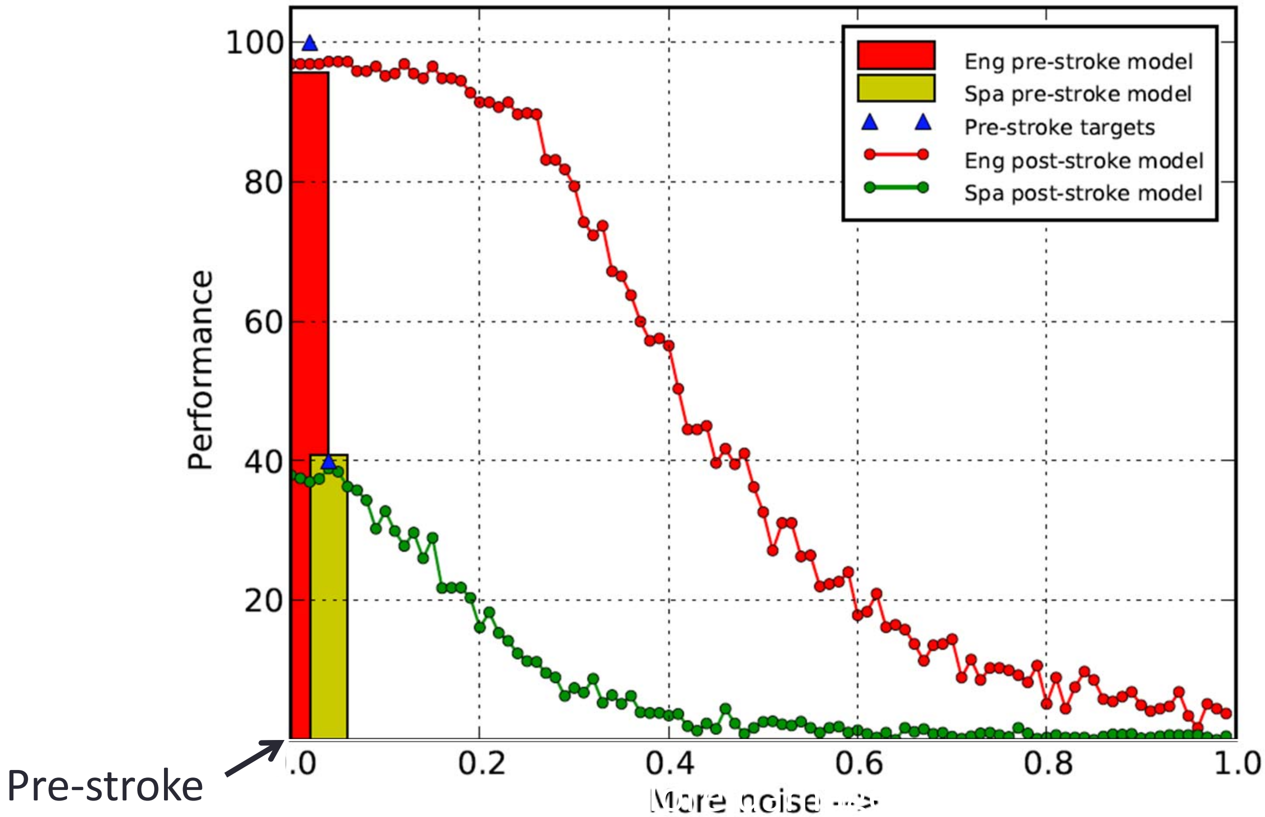
# Approach

- Lesion was applied to the connections from the semantic map to the phonetic maps
- Adding Gaussian noise with $\mu = 0$ to all these connections.
- The amount of damage (the "lesion strength") in each case was adjusted by changing the \sigma ($\sigma$) of the noise between 0 and 1.0 in steps of 0.01.
- Then, individual models of premorbid patient performance were used to investigate how damage to the model's lexicon matched actual bilingual aphasia patient naming patterns



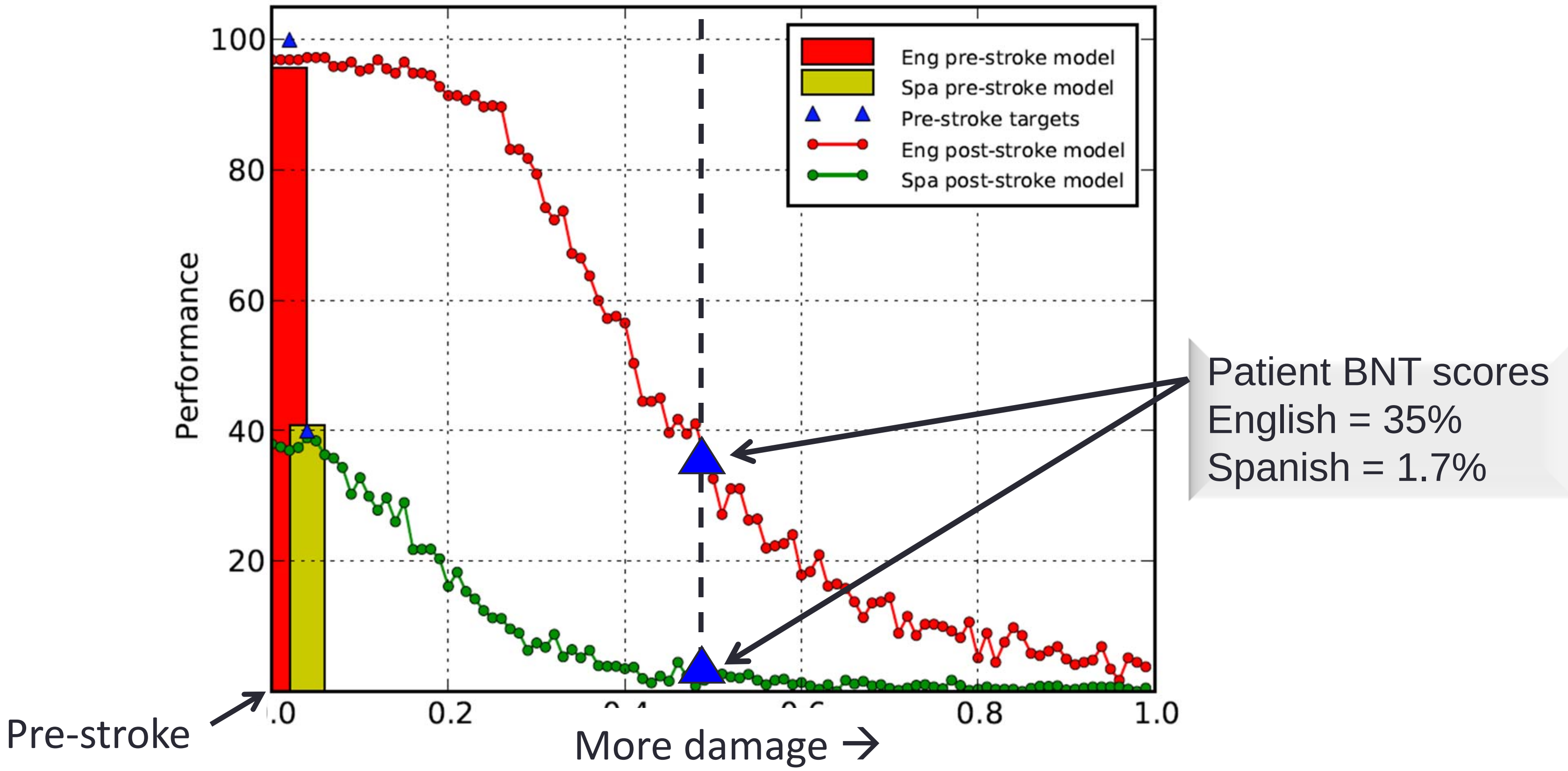

Grasemann et al., 2011; Kiran et al., 2010

# Results – Modeling Impairment in one patient




Grasemann et al., 2011; Kiran et al., 2010

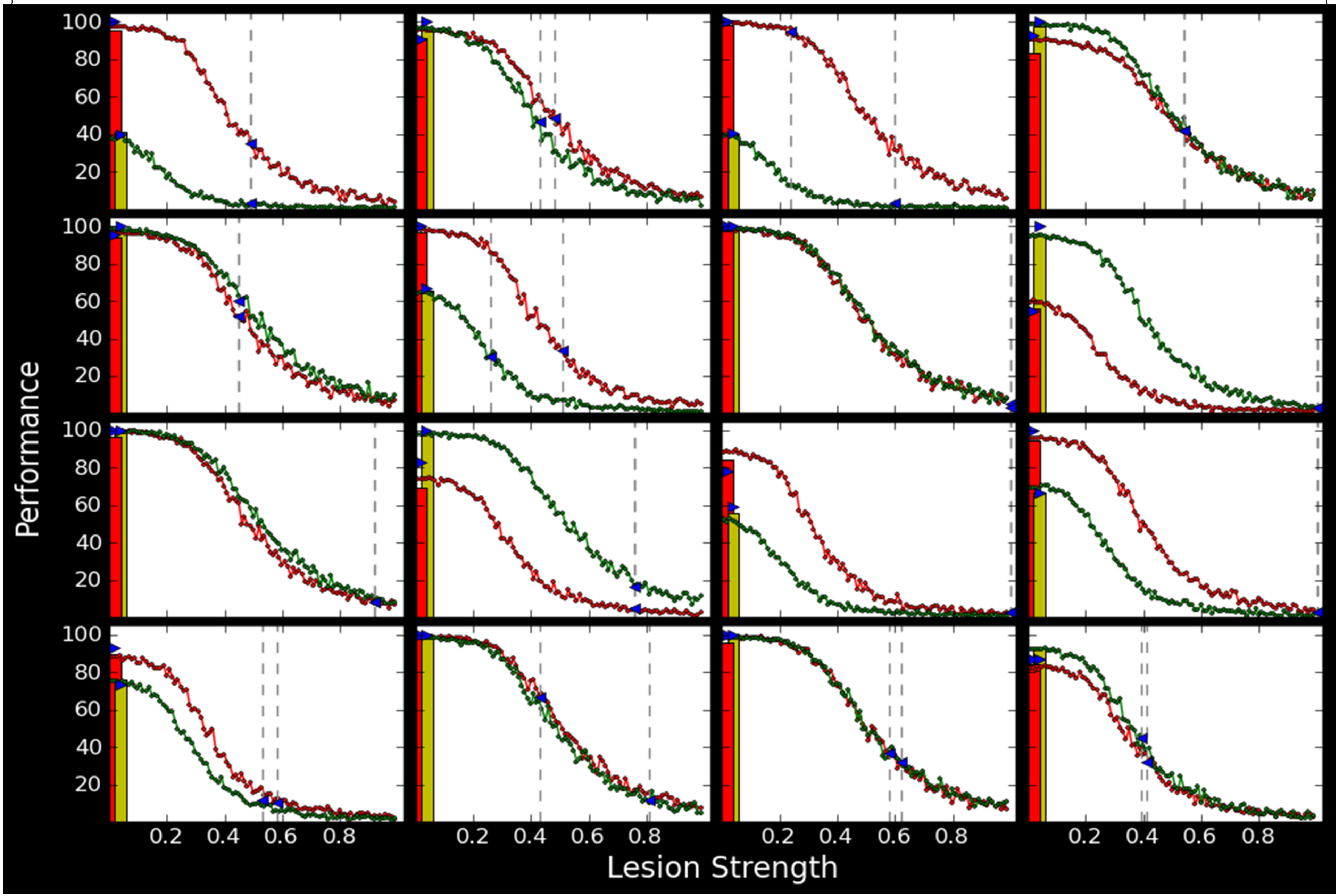
# Results – Modeling Impairment




Different pre-stroke proficiency, different level of impairment

Grasemann et al., 2011; Kiran et al., 2010

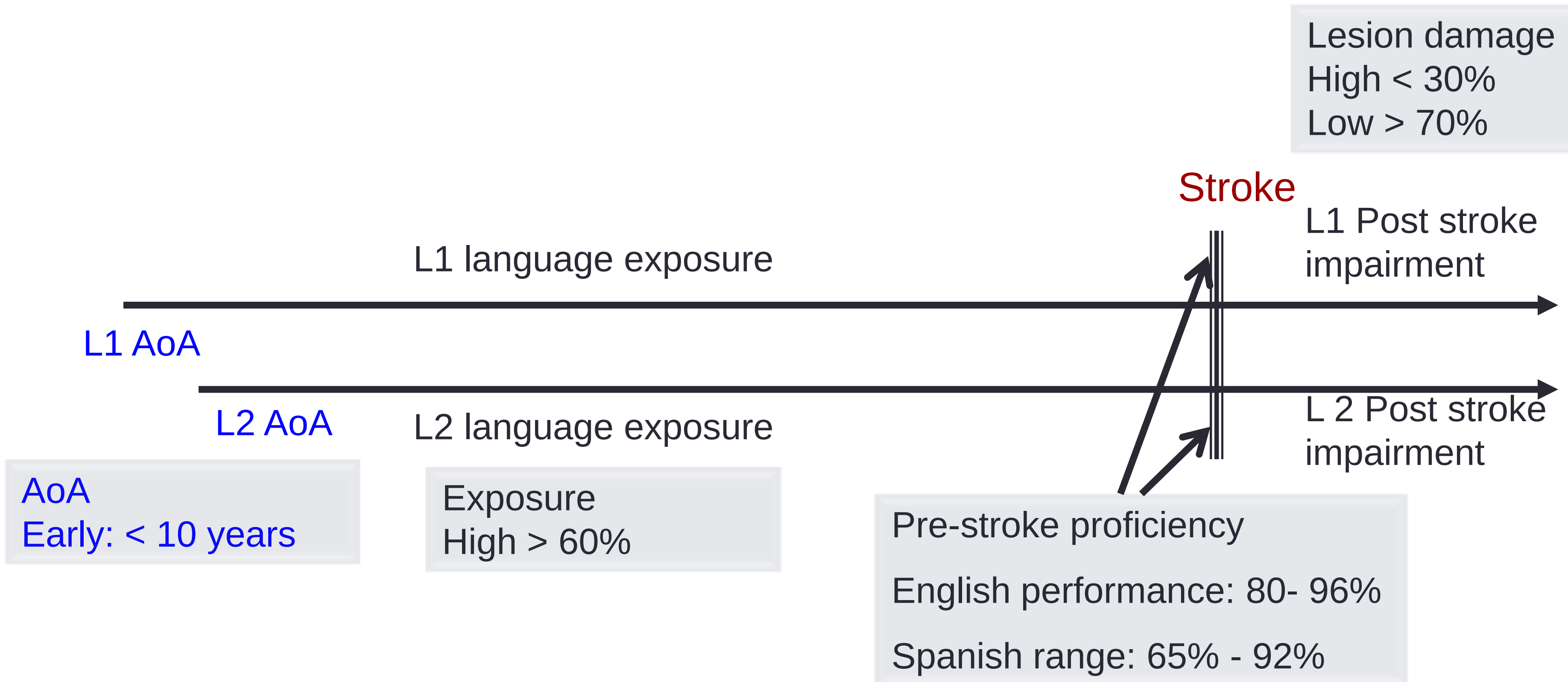
# Modeling impairment for 16 patients with aphasia



## Step 3

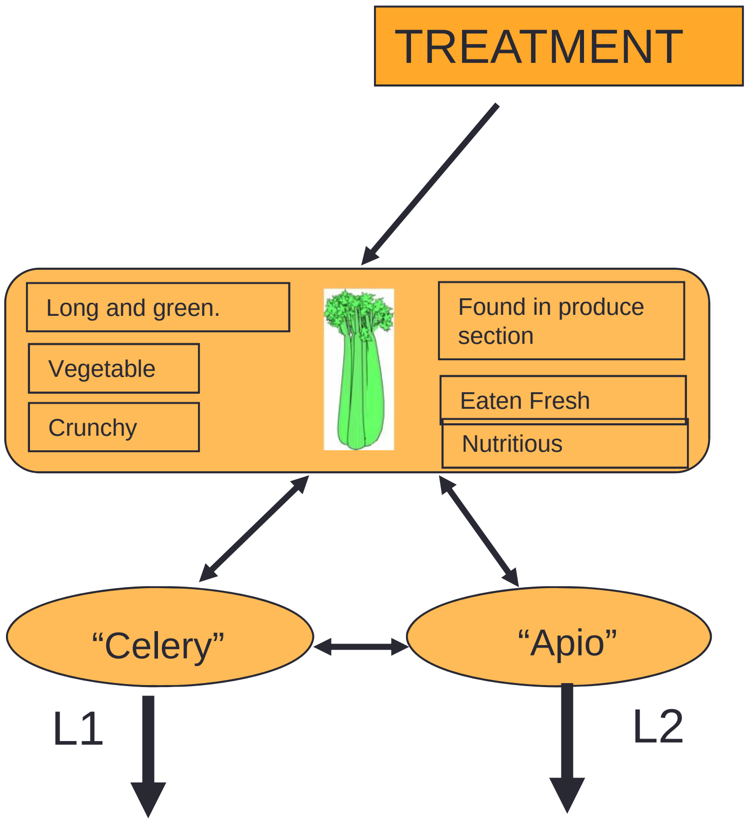
- Use the model to predict treatment outcomes
  - Examine improvements in trained language and cross language transfer

# Approach


Lesion damage
High < 30%
Low > 70%
Stroke
L1 Post stroke impairment
L1 language exposure
L1 AoA
L2 AoA
L2 language exposure
L 2 Post stroke impairment
AoA
Early: < 10 years
Exposure
High > 60%
Pre-stroke proficiency
English performance: 80- 96%
Spanish range: 65% - 92%

# Approach

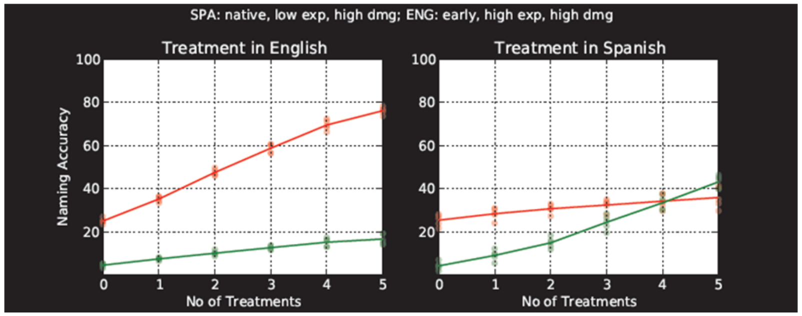
- The starting point was set to either a severe impairment in naming (30% or less accuracy) or mild impairment (70% or high naming accuracy).
- Model retrained trained with different number and schedule of presentations of words in one language
- Treatment always provided only in one language (either English/Spanish) and amount of improvement examined
- Generalization (cross language transfer) examined to untrained language

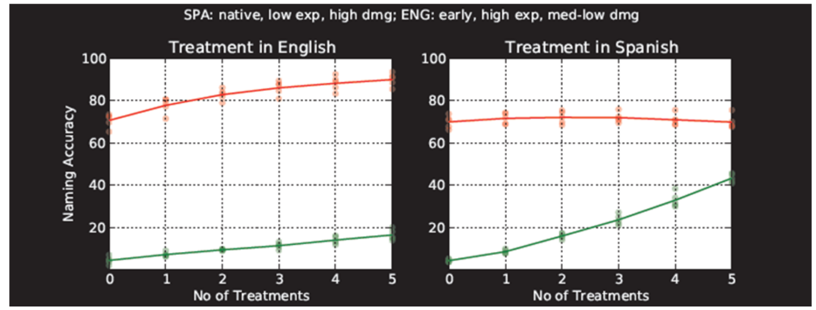


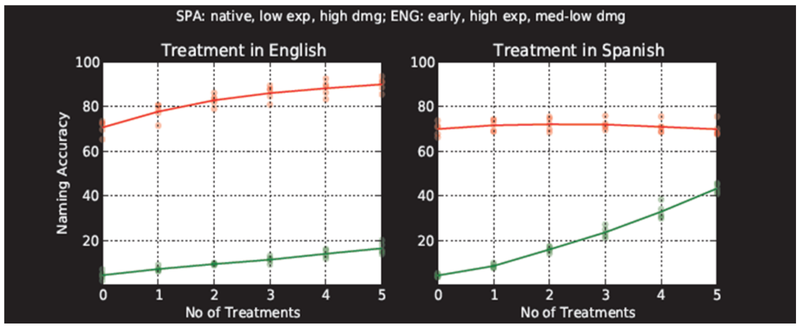

Edmonds & Kiran, 2006; Kiran & Roberts, 2009

# In order to evaluate the model

- Match the patient and model's parameters on AoA, exposure and damage parameters and see if the model's predictions match the actual data obtained.


SPA: native, low exp, high dmg; ENG: early, high exp, high dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
No of Treatments
No of Treatments


SPA: native, low exp, high dmg; ENG: early, high exp, med-low dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
No of Treatments
No of Treatments


SPA: native, low exp, high dmg; ENG: early, high exp, med-low dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
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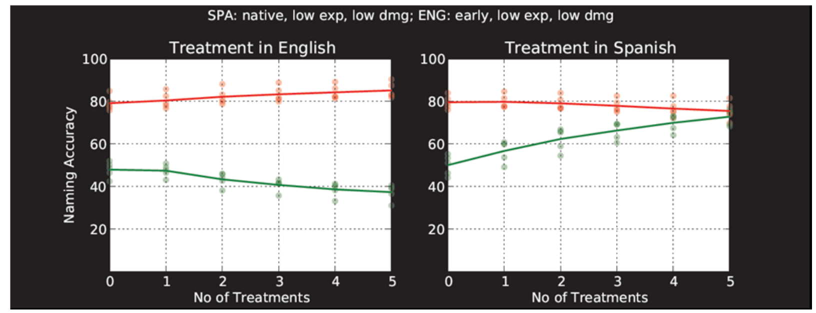
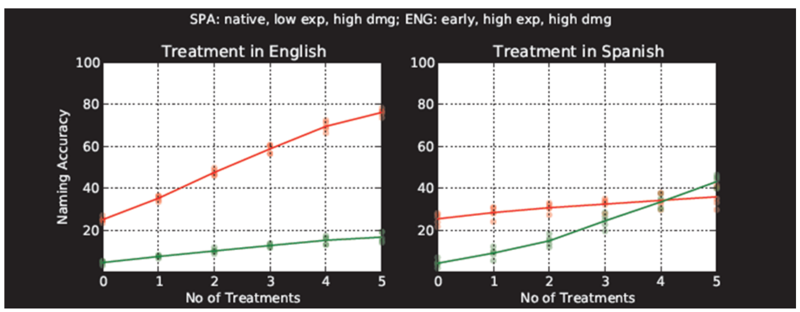
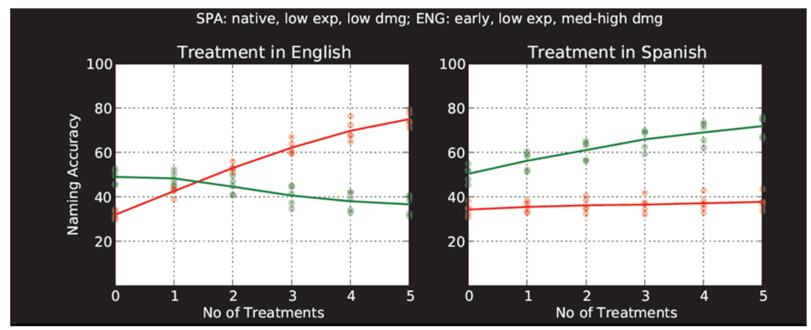
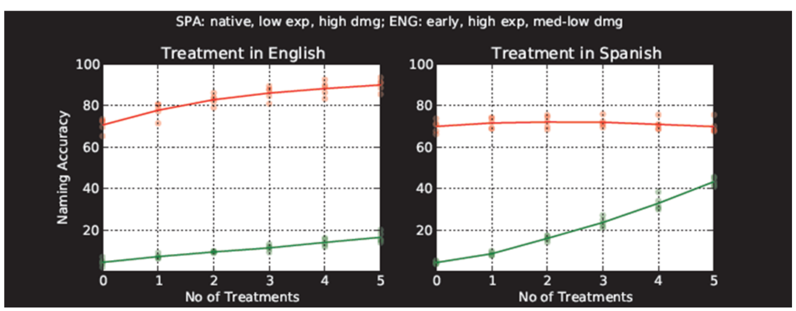
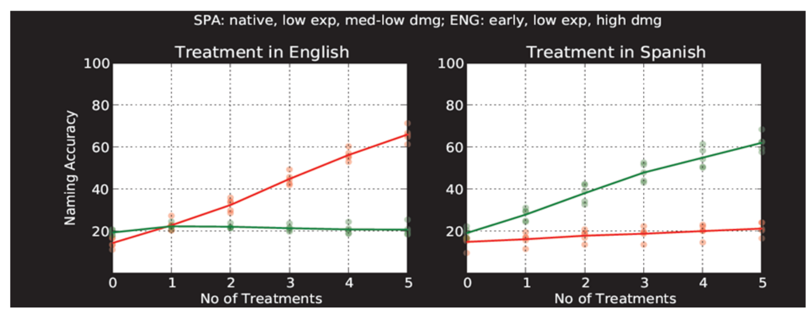

SPA: native, low exp, low dmg; ENG: early, low exp, low dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
No of Treatments
No of Treatments


SPA: native, low exp, high dmg; ENG: early, high exp, high dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
No of Treatments
No of Treatments


SPA: native, low exp, low dmg; ENG: early, low exp, med-high dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
No of Treatments
No of Treatments

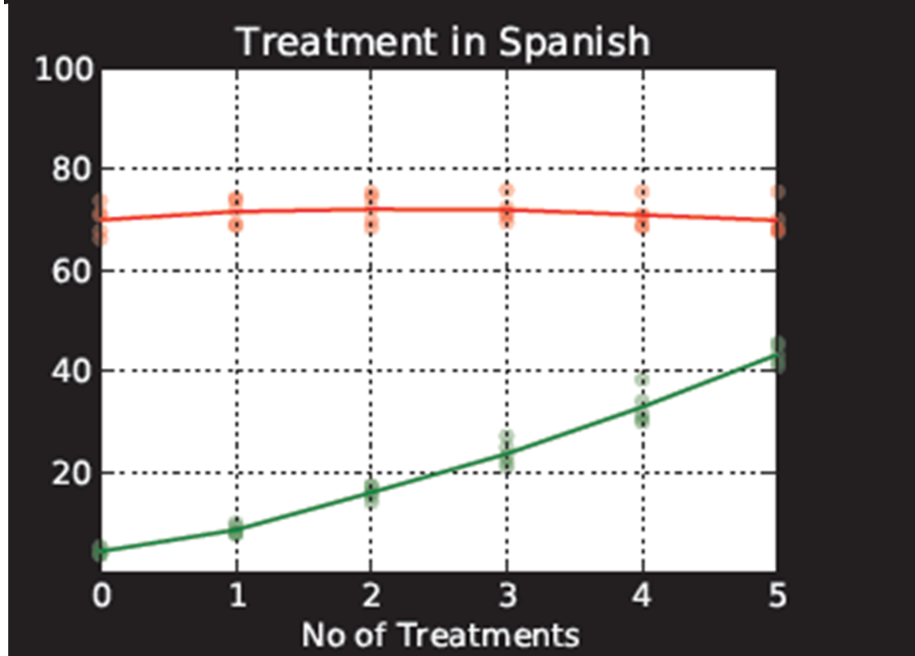

SPA: native, low exp, high dmg; ENG: early, high exp, med-low dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
No of Treatments
No of Treatments

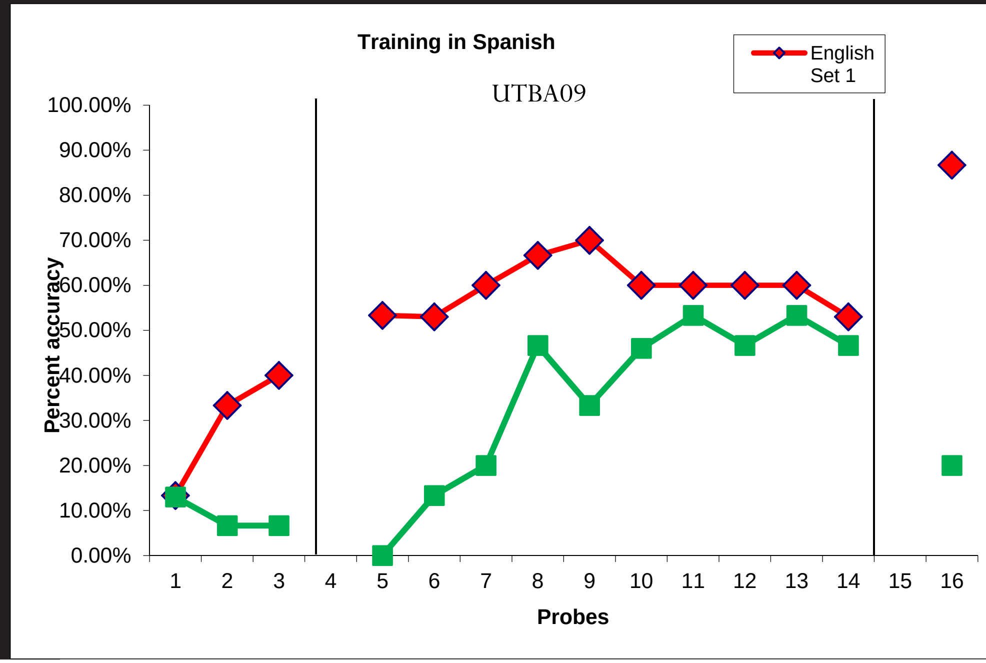

SPA: native, low exp, med-low dmg; ENG: early, low exp, high dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
No of Treatments
No of Treatments

# Patient Parameters

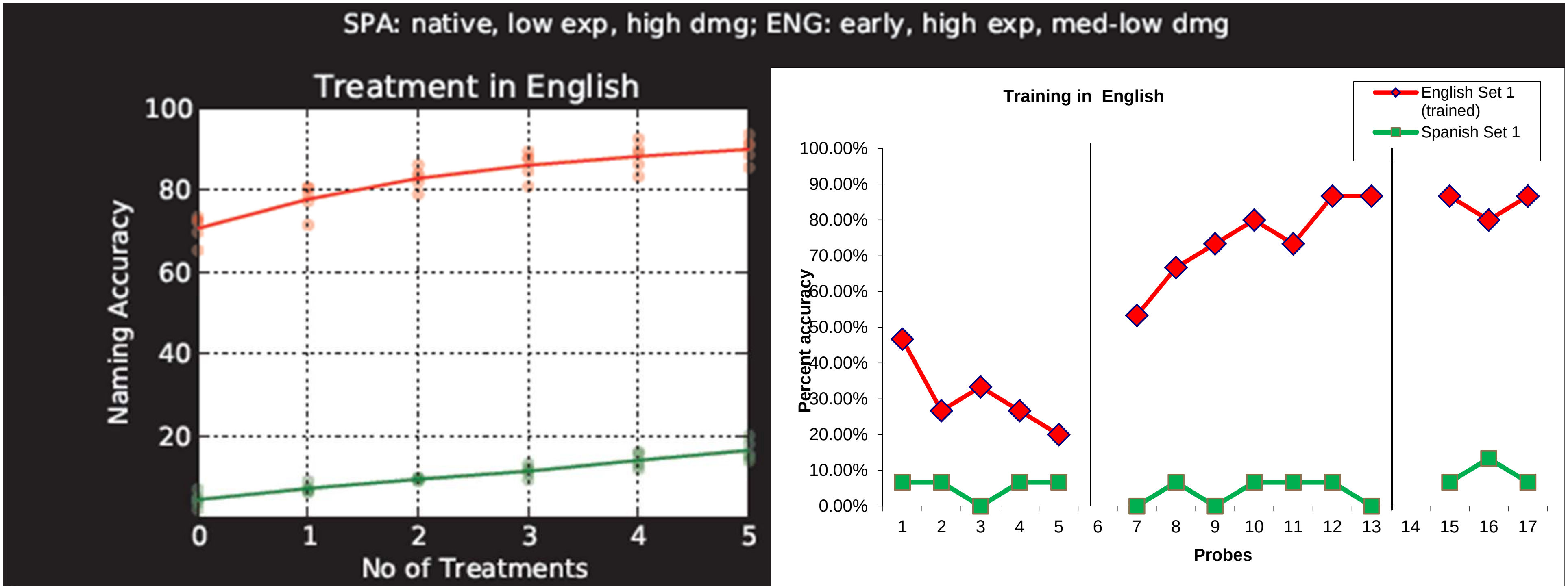
| | Spanish AoA | Spanish exposure | Spanish Damage | English AoA | Spanish exposure | Spanish Damage | Trained Language | Trained Effect size | Untrained language ES |
|---|---|---|---|---|---|---|---|---|---|
| P1 | native | low | high | early | high | high | English | 12.70 | 0.58 |
| P2 | native | low | high | early | high | high | English | 6.82 | 0.83 |
| P3 | native | low | high | early | high | low-mod | Spanish | 16.50 | 2.52 |
| P4 | native | low | high | early | high | low-mod | Spanish | 10.97 | 2.07 |
| P5 | native | low | high | early | high | low-mod | English | 5.32 | 1.19 |
| P6 | native | high | high | early | low | high | Spanish | 13.84 | 10.68 |
| P7 | native | high | high | late | low | high | English | 2.89 | 4.08 |
| P8 | native | high | high | late | low | high | Spanish | 0.00 | 0.00 |
| P9 | native | high | high | late | low | high | English | 0.00 | 0.00 |
| P10 | native | high | mod-high | late | low | high | English | 1.44 | 4.90 |
| P11 | native | high | mod-high | late | low | high | Spanish | 12.73 | 1.89 |
| P12 | native | high | mod-high | late | low | mod-high | English | 4.92 | 1.42 |
| P13 | native | high | mod-high | late | low | mod-high | Spanish | 11.08 | 4.95 |
| P14 | native | mod | high | late | mod | high | English | 14.90 | 1.15 |
| P16 | native | mod | mod-high | late | mod | high | Spanish | 15.17 | 1.73 |
| P17 | native | no data | high | early | no data | high | Spanish | 12.41 | 3.11 |

SPA: native, low exp, high dmg; ENG: early, high exp, med-low dmg

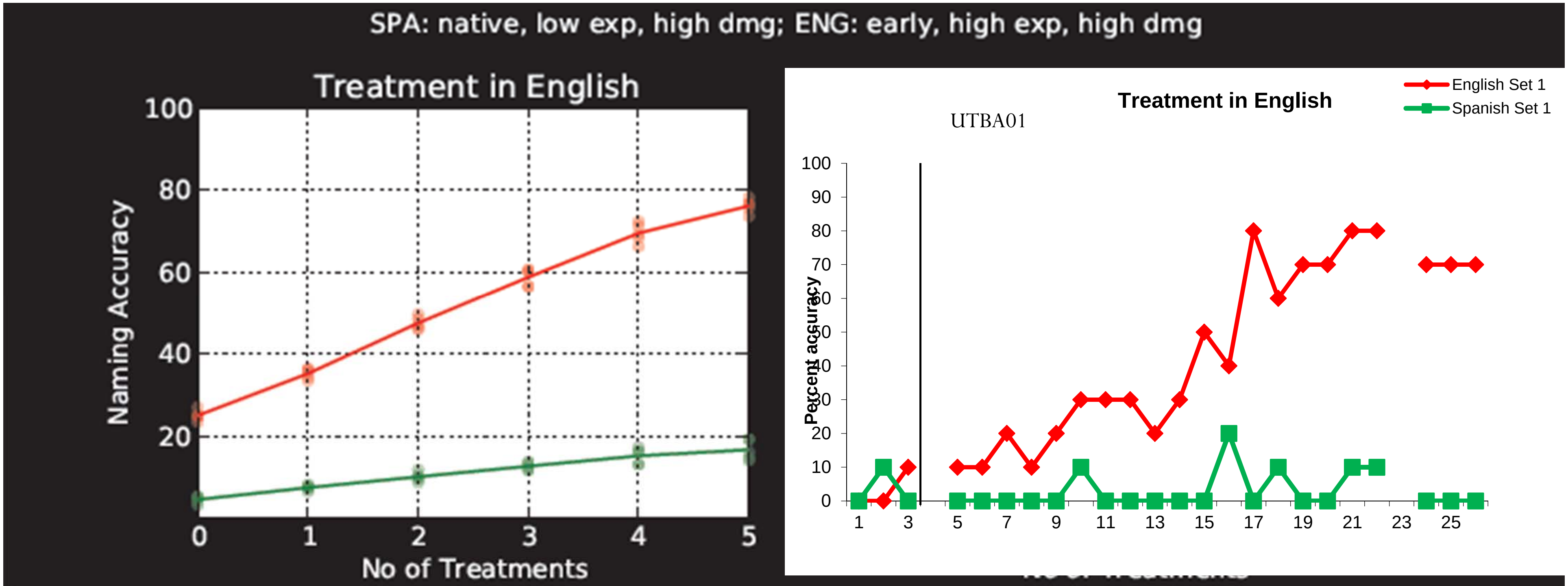


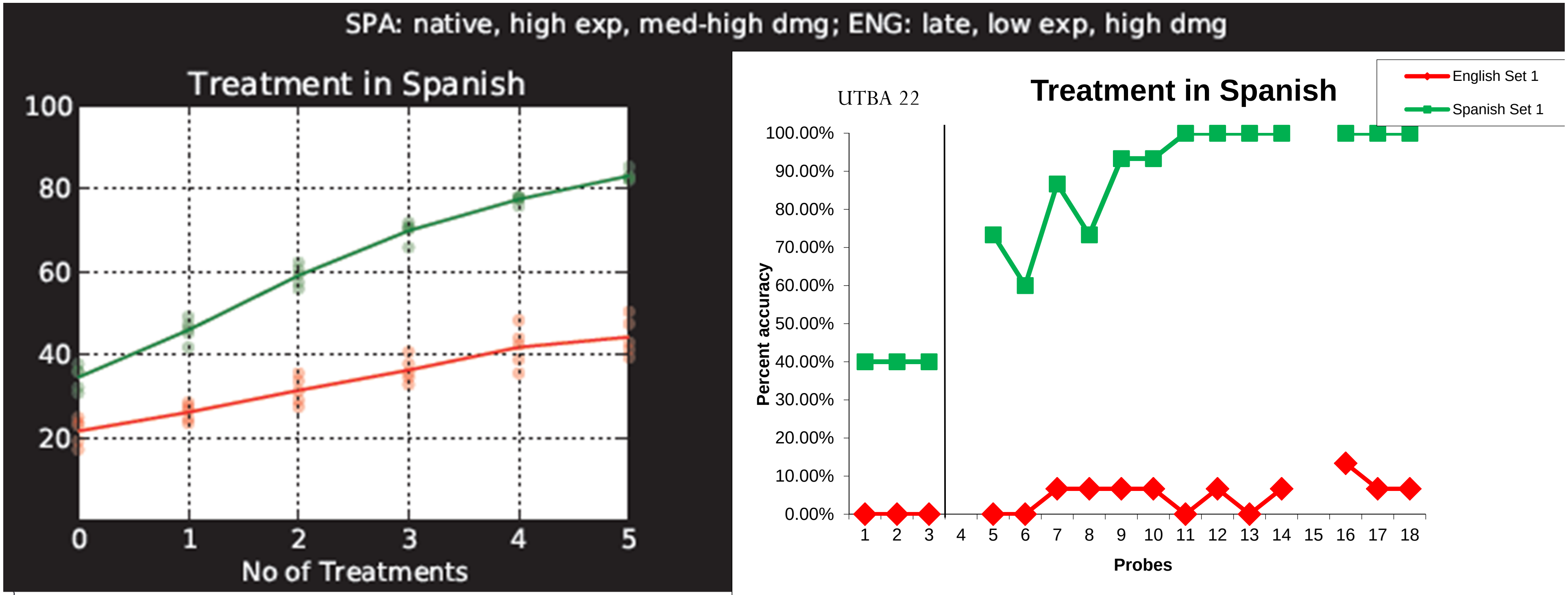

UTBA 09:
Spanish ES: 10.97
English ES: 2.07



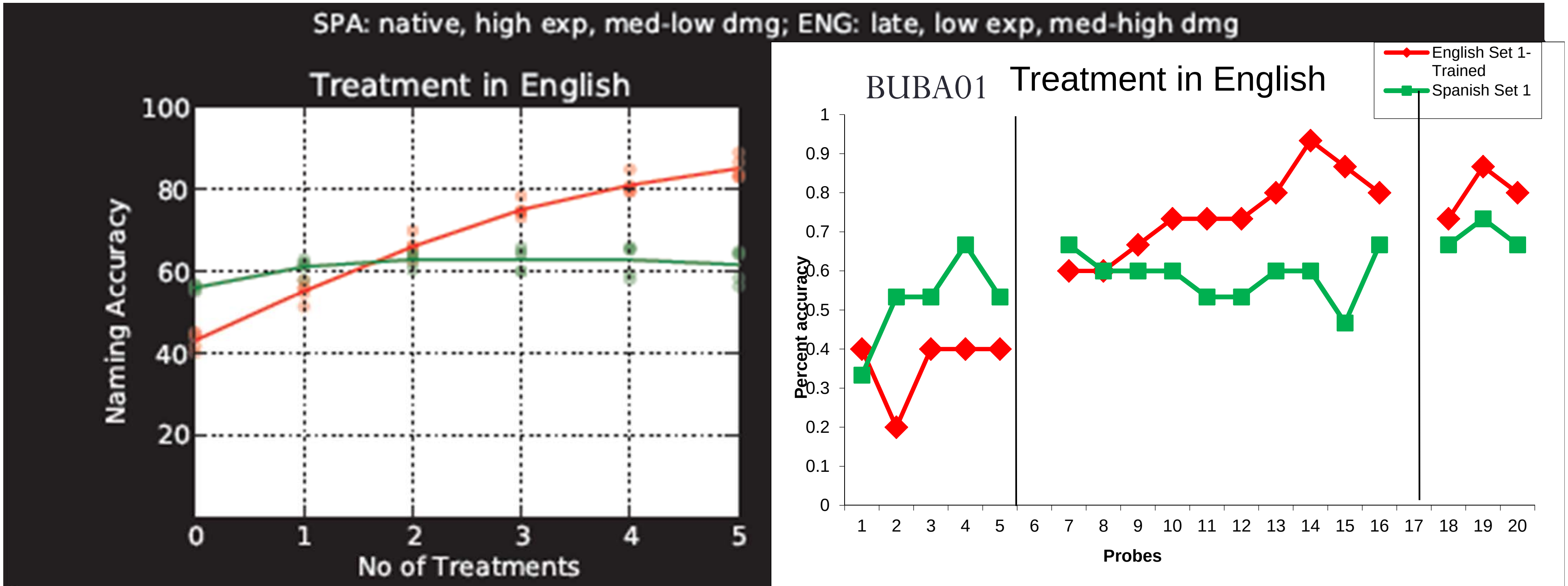

UTBA 17:
Spanish ES: 5.32
English ES: 1.19




UTBA 01:
Spanish ES: .58
English ES: 12.7

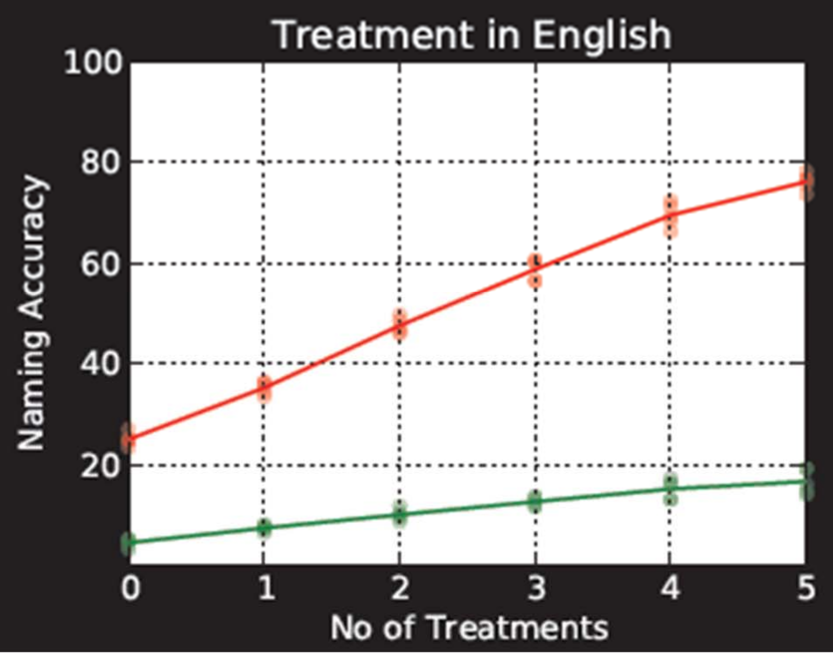


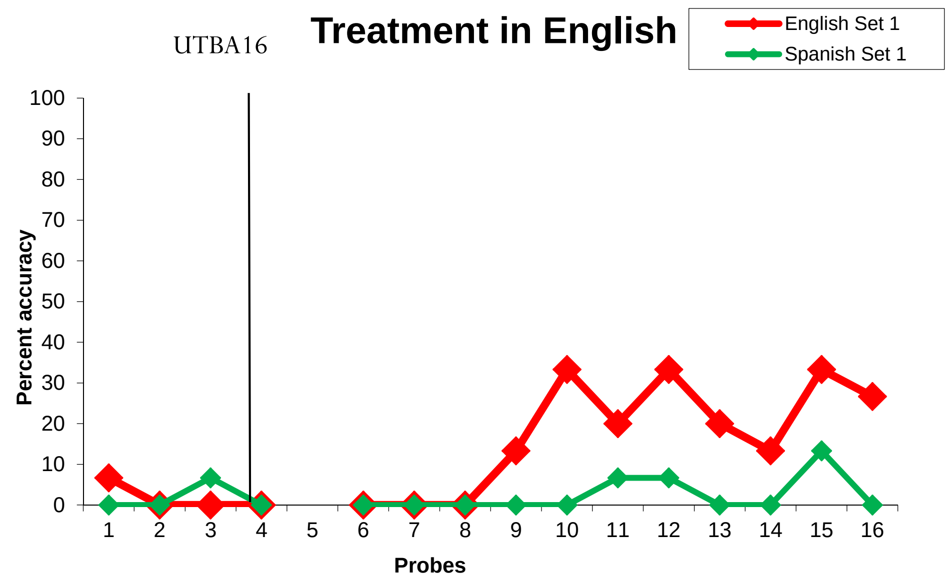

UTBA 22:
Spanish ES: 12.7
English ES: 1.89



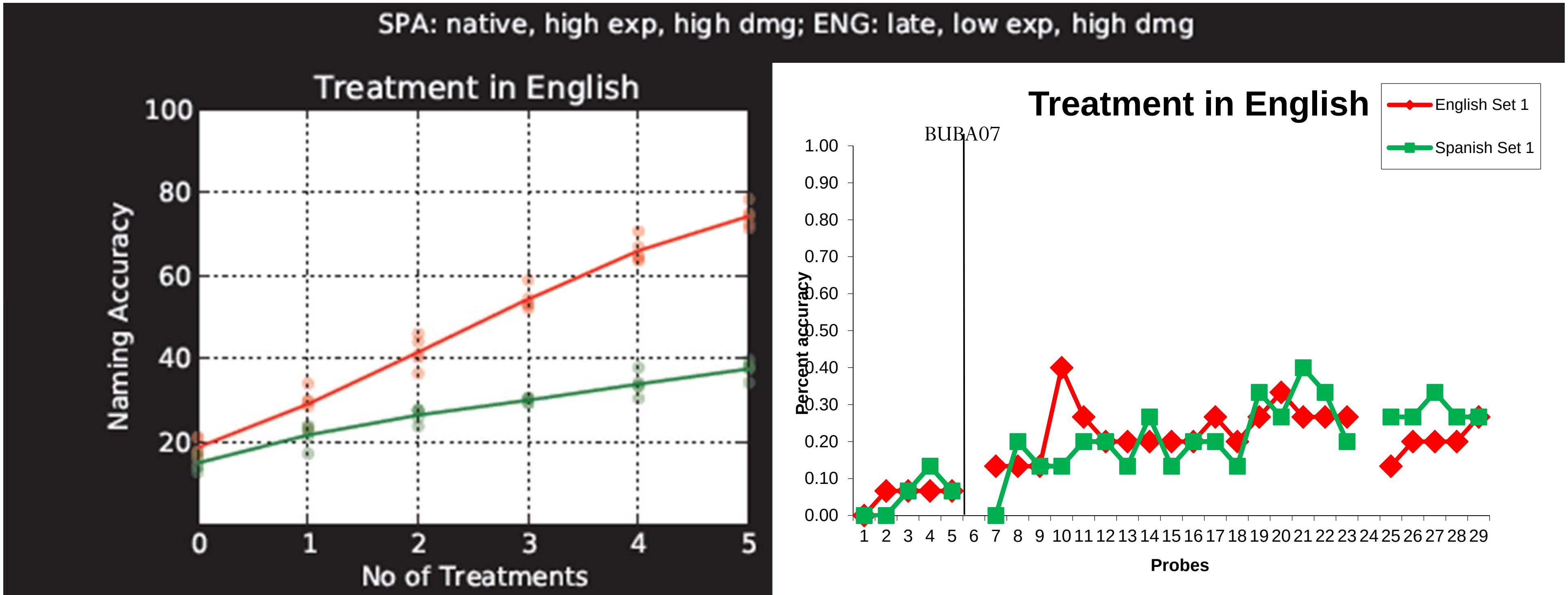

BUBA01
Spanish ES: 1.42
English ES: 4.92

SPA: native, low exp, high dmg; ENG: early, high exp, high dmg




UTBA16:
Spanish ES: .83
English ES: 6.8



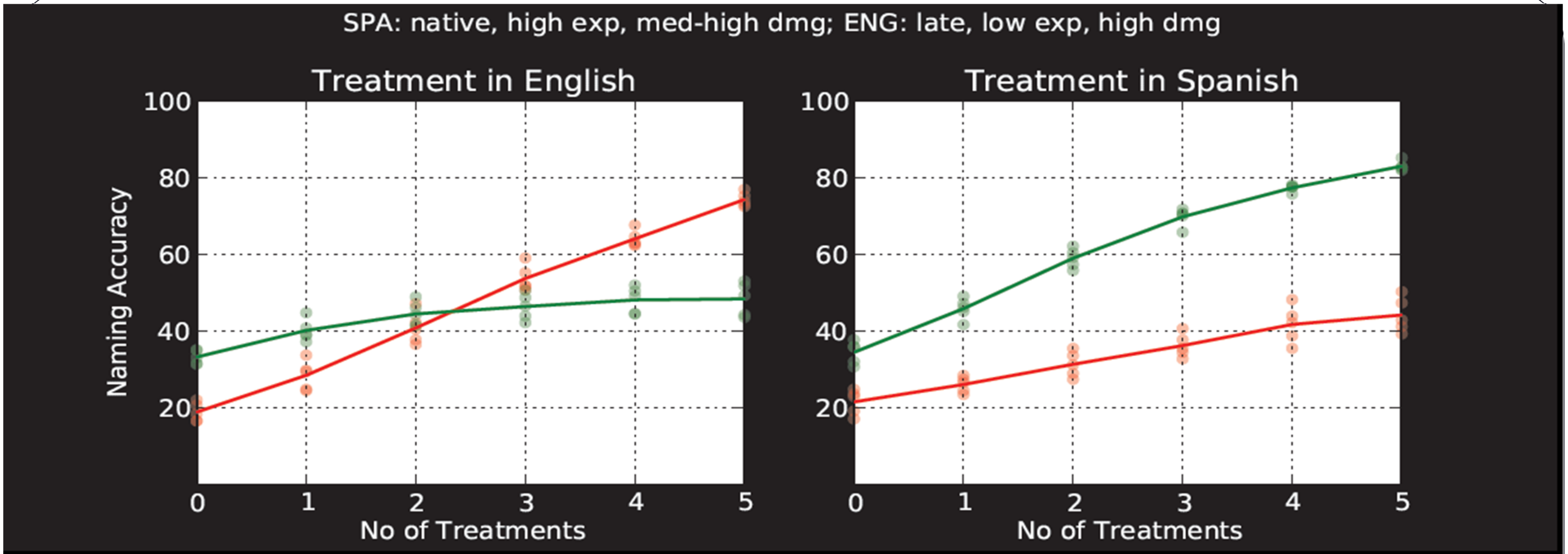

BUBA07
Spanish ES: 4.08
English ES: 2.8

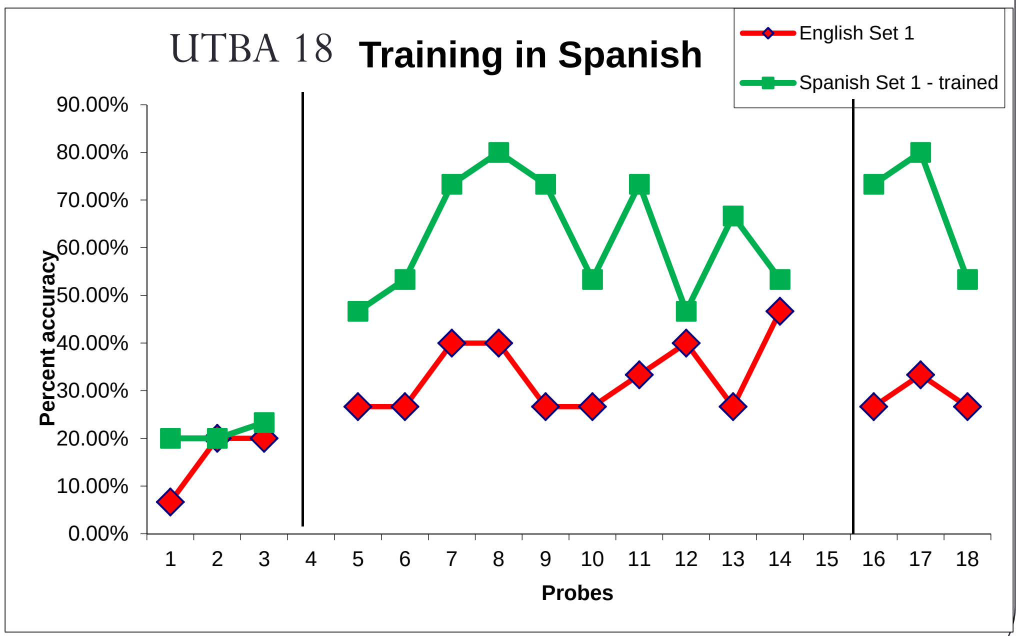
# Summary

- Model can predict rehabilitation outcomes
  - Of the 16 patients, good fit for 11 patients,
  - For patients that do not have a good fit 5/16, model overestimates outcomes for 3 of them
  - Provides a starting point for understanding why patient did not improve

- Curve fitting analysis ongoing-can evaluate the extent of match.

- Model can also predict what treatment outcome may have been if treatment plan was different that what was followed…


SPA: native, high exp, med-high dmg; ENG: late, low exp, high dmg
Treatment in English
Treatment in Spanish
Naming Accuracy
100
80
60
40
20
0
1
2
3
4
5
No of Treatments


UTBA 18
Training in Spanish
English Set 1
Spanish Set 1 - trained
Percent accuracy
90.00%
80.00%
70.00%
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
Probes

# Conclusions and future directions

- While preliminary, results from this project allows a direct comparison of outcomes using two parallel yet complementary scientific approaches.

- The combination of computational modeling and behavioral treatment provide a promising approach to examining the important issue of recovery of language in bilingual aphasia

- In future, we are refining our ability to describe our own patients in terms of exposure, proficiency and impairment- which in of itself can help us better understand bilingual aphasia.

Uli Grasemann
UT-Austin

Risto Miikkulainen
UT-Austin

Chaleece Sandberg
Boston University

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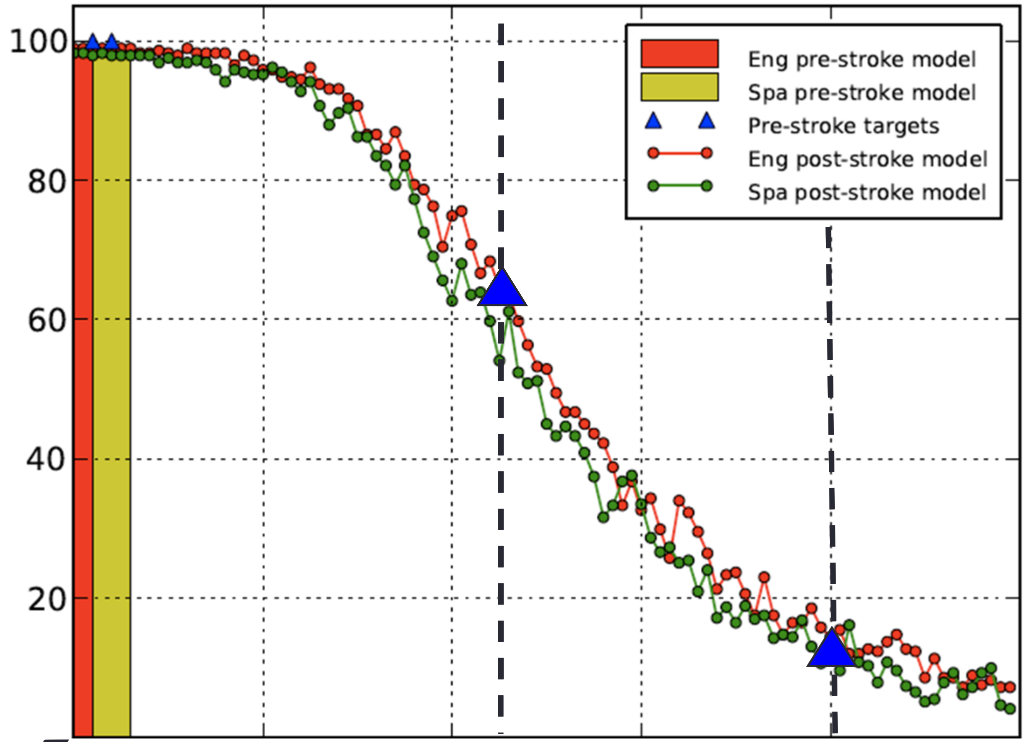
- UT Austin
  - Anne Alvarez
  - Ellen Kester
  - Rajani Sebastian
- Boston University
  - Danielle Tsibulsky
  - Fabiana Cabral
  - Lauren Liria
  - Teresa Gray

# Results – Modeling Impairment in a different patient



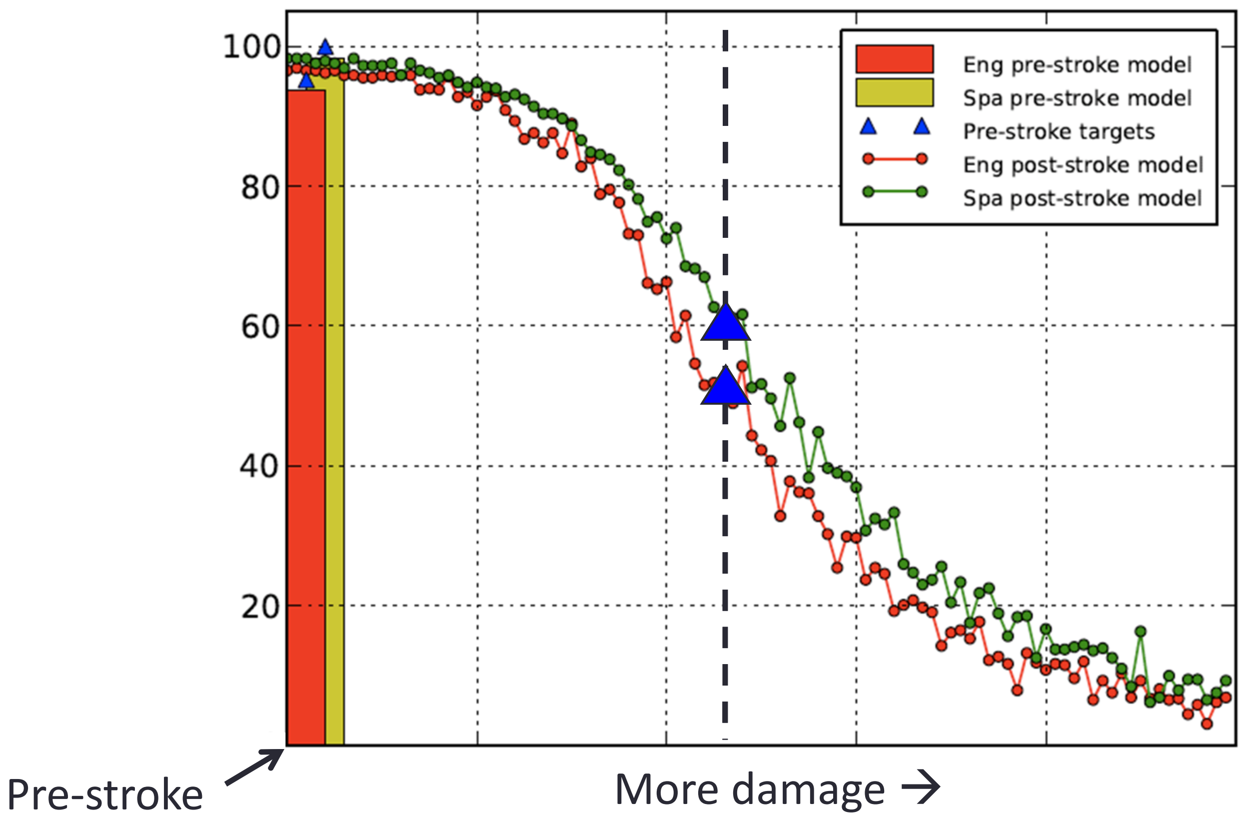

Pre-stroke

More damage →

Similar pre-stroke proficiency, different level of impairment

Grasemann et al., 2011; Kiran et al., 2010

# Results – Modeling Impairment in a third patient




Similar pre-stroke proficiency, same level of impairment

Impairment of 12/15 patients modeled well with symmetric damage