How has the Brazilian Amazon been constructed as a problem - presidential speeches and transnational politics since 1985

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We need to protect the Amazon from foreign interests.

We need to exploit the Amazon's natural resources.

We need to provide better living standards for the people in the Amazon.

We need to preserve the Amazon as a standing ecosystem.

```
knitr::include_graphics("amazon_basin.jpeg")
```

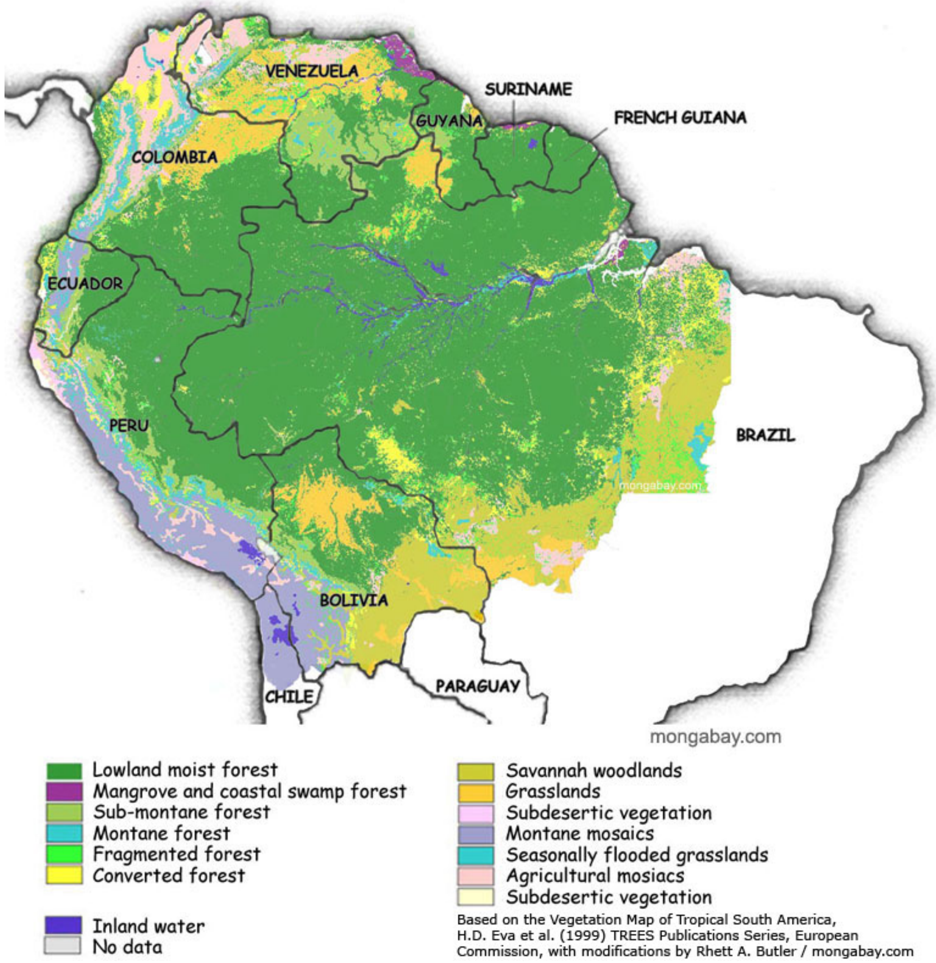

Figure 1: The Amazon Forest

Question

How the Brazilian Amazon has been constructed as a problem in transnational presidential speeches since 1985?

Data and methods

- Dataset containing all 6130 official speeches by presidents since 1985
- Subset of 2014 “amazonian statements”
- Location
- Hand-coding and supervised machine learning
- Can you think of some limitations with this?

```
knitr::include_graphics("figure1pic.png")
```

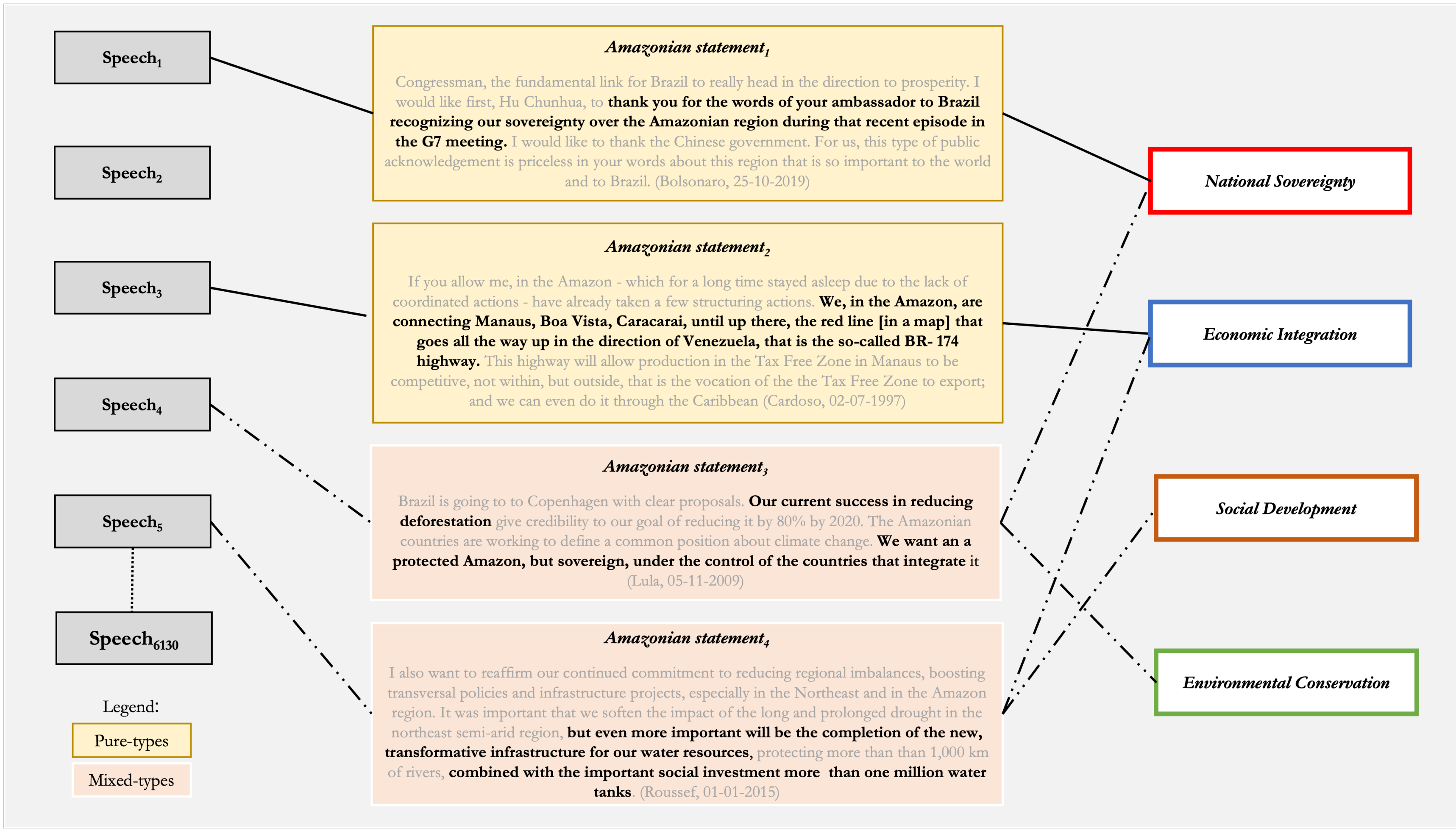

Figure 2: Operationalization of problem-constructions

A simple logistic regression

Why do we use a logistic model and not a linear one here?

```
ama_model <- dplyr::left_join(ama_mx, amazon_def_year, by = "year") #merge
ama_model <- dplyr::left_join(ama_model, AAI, by = "year") #merge
ama_model <- filter(ama_model, location_cat != "Non Identified",
                    mx_cat != "Other Mixed-types") %>%
  mutate(con_vs_all = ifelse(mx_cat == "Pure Environmental Conservation", 1, 0),
         EI_vs_all = ifelse(mx_cat == "Pure Economic Integration", 1, 0),
         SD_vs_all = ifelse(mx_cat == "Pure Social Development", 1, 0),
         sov_vs_all = ifelse(mx_cat == "Pure National Sovereignty", 1, 0))
#model
model_logit_con <- glm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                   family=binomial(link = "logit"), data = ama_model)
summary(model_logit_con)
```

```
##
## Call:
## glm(formula = con_vs_all ~ km_to_manaus + election_year + def_year +
##     AAI, family = binomial(link = "logit"), data = ama_model)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3118  -0.5825  -0.5130  -0.4377   2.3245
##
## Coefficients:
##                  Estimate  Std. Error z value             Pr(>|z|)
## (Intercept)   -1.71845866  0.19066729  -9.013 < 0.0000000000000002 ***
## km_to_manaus   0.00011555  0.00002145   5.386         0.0000000719 ***
## election_year  0.28790781  0.15665954   1.838             0.066093 .
## def_year      -0.03173895  0.01129821  -2.809             0.004966 **
## AAI            0.00038679  0.00010404   3.718             0.000201 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1549.3  on 1841  degrees of freedom
## Residual deviance: 1497.3  on 1837  degrees of freedom
## AIC: 1507.3
##
## Number of Fisher Scoring iterations: 4
```

Need an easy publication table?

```r
con_model <- stargazer::stargazer(model_logit_con, header = FALSE)
```

Table 1:

	Dependent variable:
	con_vs_all
km_to_manaus	0.0001^{***}
	(0.00002)
election_year	0.288^{*}
	(0.157)
def_year	-0.032^{***}
	(0.011)
AAI	0.0004^{***}
	(0.0001)
Constant	-1.718^{***}
	(0.191)
Observations	1,842
Log Likelihood	−748.648
Akaike Inf. Crit.	1,507.296
Note:	*p<0.1; **p<0.05; ***p<0.01

What are log-odds

What about time effects?

Does time matter?

```r
ols <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                data = ama_model, model = "pooling", index = c("year"))
fixed <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                data = ama_model, model = "within", index = c("year"))
random <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                   data = ama_model, model = "random", index = c("year"))
summary(ols)
```

```
## Pooling Model
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
##     def_year + AAI, data = ama_model, model = "pooling", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
```

```
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -0.470289 -0.158090 -0.126625 -0.082295  0.953062
##
## Coefficients:
##                    Estimate    Std. Error t-value       Pr(>|t|)
## (Intercept)    0.1429802958  0.0235559575  6.0698 0.000000001552 ***
## km_to_manaus   0.0000178431  0.0000032303  5.5237 0.000000037934 ***
## election_year  0.0359069945  0.0199552120  1.7994      0.0721228 .
## def_year      -0.0033476666  0.0012965902 -2.5819      0.0099026 **
## AAI            0.0000552053  0.0000146958  3.7565      0.0001776 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    233.24
## Residual Sum of Squares: 226.09
## R-Squared:      0.030665
## Adj. R-Squared: 0.028555
## F-statistic: 14.5286 on 4 and 1837 DF, p-value: 0.00000000001099
```

```
summary(fixed)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
##     def_year + AAI, data = ama_model, model = "within", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -0.729676 -0.166751 -0.117960 -0.045981  0.970345
##
## Coefficients:
##                  Estimate   Std. Error t-value    Pr(>|t|)
## km_to_manaus 0.0000152831 0.0000033197  4.6037 0.000004441 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    220.46
## Residual Sum of Squares: 217.9
## R-Squared:      0.011612
## Adj. R-Squared: -0.0086599
## F-statistic: 21.194 on 1 and 1804 DF, p-value: 0.0000044405
```

```
summary(random)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
```

```
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
##     def_year + AAI, data = ama_model, model = "random", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
##
## Effects:
##                    var  std.dev share
## idiosyncratic 0.120789 0.347547 0.981
## individual    0.002288 0.047836 0.019
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00934 0.26150 0.35206 0.33835 0.42343 0.47400
##
## Residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.46769 -0.16706 -0.12348 -0.00009 -0.07395  0.95696
##
## Coefficients:
##                    Estimate    Std. Error z-value     Pr(>|z|)
## (Intercept)    0.1648304527  0.0331734180  4.9688 0.0000006739 ***
## km_to_manaus   0.0000166369  0.0000032727  5.0835 0.0000003706 ***
## election_year  0.0271240068  0.0298012337  0.9102      0.36274
## def_year      -0.0044176296  0.0018997506 -2.3254      0.02005 *
## AAI            0.0000516826  0.0000220758  2.3411      0.01922 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    228.22
## Residual Sum of Squares: 223.14
## R-Squared:      0.022236
## Adj. R-Squared: 0.020107
## Chisq: 38.5979 on 4 DF, p-value: 0.000000084344
```

The Amazon multi-level game: talking to the people inside

Can you see the relationship?

```
# other models
model_logit_ei <- glm(EI_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                     family=binomial(link = "logit"), data = ama_model)
model_logit_sd <- glm(SD_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                     family=binomial(link = "logit"), data = ama_model)
model_logit_sov <- glm(sov_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                     family=binomial(link = "logit"), data = ama_model)
#Plot model
ama_model$"Environmental Conservation" = predict(model_logit_con, ama_model, type = "response")
ama_model$"Economic Integration" = predict(model_logit_ei, ama_model, type = "response")
ama_model$"Social Development" = predict(model_logit_sd, ama_model, type = "response")
ama_model$"National Sovereignty" = predict(model_logit_sov, ama_model, type = "response")
plot_loc <- ama_model %>% gather(key=p_c, value = pred, 22:25)
plot_loc$p_c <-factor(plot_loc$p_c, levels = c("Economic Integration",
                                               "Environmental Conservation",
                                               "Social Development",
                                               "National Sovereignty"))
ggplot(plot_loc, aes(x = km_to_manaus, y=pred, color=p_c)) +
  geom_jitter(alpha=1, size=1) +
  geom_smooth(size = .5, se=FALSE) +
  scale_y_continuous(labels = percent_format()) +
  labs(x = "Distance from the Amazon (km)",
       y = "",
       title = "Predicted probability of each problem-construction as a function of distance from the Am
       caption = "Curves in the plots are estimated using loess method.") +
  theme(text = element_text(size=11,  family="Times"),
        panel.background = element_rect("white", "black", .5, "solid"),
                  panel.grid.major = element_line(color = "grey", linewidth = 0.2,
                                                  linetype = "solid"),
        axis.text = element_text(color = "black", size = 11),
        title = element_text(color = "black", size = 12, face = "bold"),
        legend.title = element_blank(),
        plot.subtitle = element_text(color = "black", size = 11, face = "plain"),
        legend.position = "none") +
  facet_wrap(~p_c, ncol=2)
```

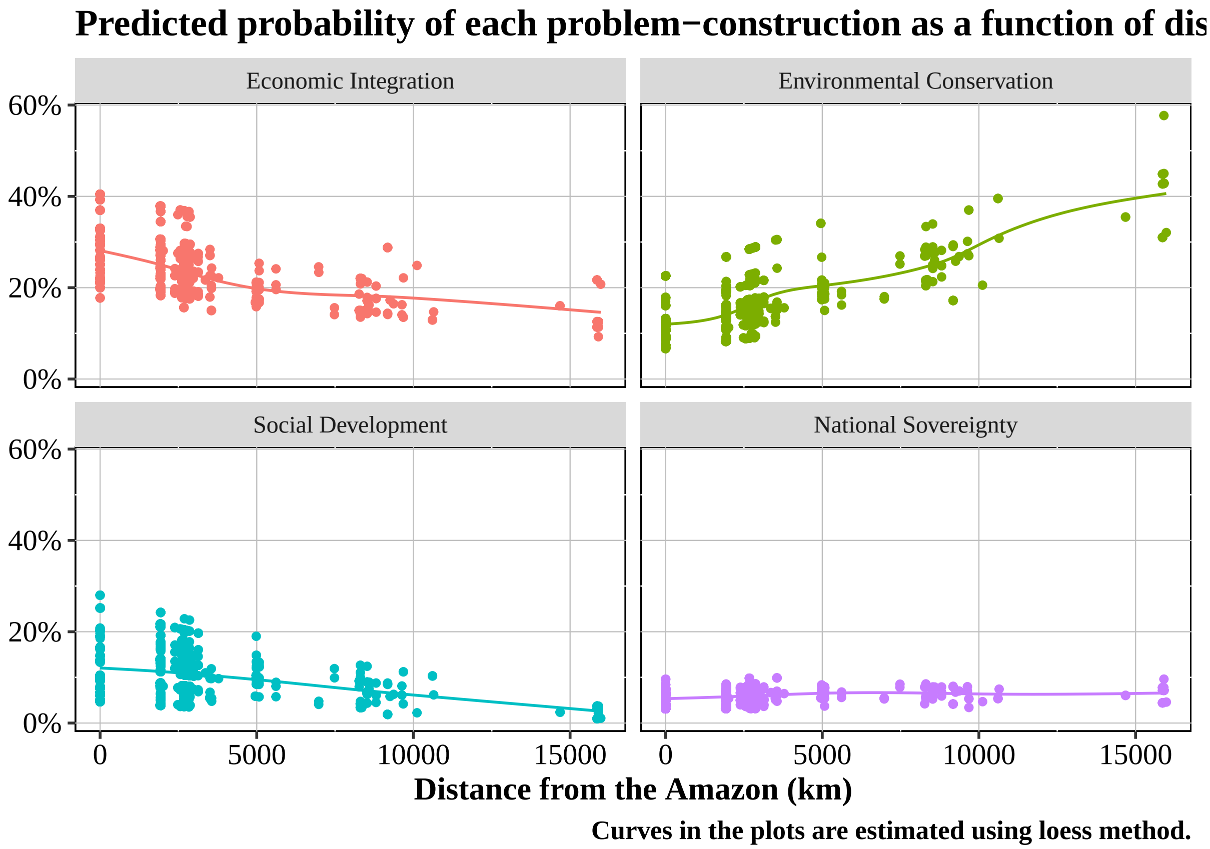

Figure 3: Logistic Regression predicted values

The Amazon multi-level game: boasting policy outside

Why should we divide distances to Manaus?

```r
ama_model$thousand_km<- ama_model$km_to_manaus/1000
model_logit_con2 <- glm(con_vs_all ~ thousand_km + election_year + def_year + AAI,
                   family=binomial(link = "logit"), data = ama_model)
model_logit_ei2 <- glm(EI_vs_all ~ thousand_km + election_year + def_year + AAI,
                   family=binomial(link = "logit"), data = ama_model)
model_logit_sd2 <- glm(SD_vs_all ~ thousand_km + election_year + def_year + AAI,
                   family=binomial(link = "logit"), data = ama_model)
model_logit_sov2 <- glm(sov_vs_all ~ thousand_km + election_year + def_year + AAI,
                   family=binomial(link = "logit"), data = ama_model)
md <- stargazer::stargazer(model_logit_con2, model_logit_ei2, model_logit_sd2,
                          model_logit_sov2, digits = 6, header = FALSE,
                          dep.var.labels = c("Conservation", "Economic Integration",
                                             "Social Development", "Sovereignty"),
                          covariate.labels = c("Distance from the Amazon in 1000s of km",
                                               "Election year", "Yearly Deforestation",
                                               "Yearly   Inflation"), no.space = TRUE,
                          title = "Logistic Regression Models")
```

Table 2: Logistic Regression Models

	Dependent variable:		
	Conservation	Economic Integration	Social Development
	(1)	(2)	(3)
Distance from the Amazon in 1000s of km	0.115554***	−0.056590**	−0.101285**
	(0.021453)	(0.023979)	(0.039849)
Election year	0.287908*	−0.022328	0.328917*
	(0.156660)	(0.132762)	(0.171163)
Yearly Deforestation	−0.031739***	0.040870***	−0.072349***
	(0.011298)	(0.008404)	(0.013232)
Yearly Inflation	0.000387***	−0.000231**	−0.000205
	(0.000104)	(0.000104)	(0.000151)
Constant	−1.718459***	−1.568837***	−0.909845***
	(0.190667)	(0.159988)	(0.213791)
Observations	1,842	1,842	1,842
Log Likelihood	−748.648200	−1,022.790000	−620.264400
Akaike Inf. Crit.	1,507.296000	2,055.579000	1,250.529000
Note:			*p<0.1; **p<0.0