# Chimpanzee Gesture Ngrams

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# 1 Predictability of next elements in chimpanzee gesture sequences

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#### 1.1 Abstract

Abstract Recent research has produced evidence for basic combinatorial abilities in the vocal systems of different animal species. Here, we investigate the structure of gesture sequences in Eastern chimpanzees (Pan troglodytes schweinfurthii) to detect whether gestural communication shows non-random combinations and how combinatorial rules influence predictability. As the parsing of signals into sequences is dependent on researcher decisions, we employ a multiverse approach, considering four different definitions of what constitutes a 'sequence' based on varying time thresholds. Our results indicate that sequences tend to be short (even with the most liberal time window) and that transitions between some gesture types occur more frequently than expected by chance, with some transitions showing significant association across all time windows. These transitions often involve repetition, suggesting persistence as a key aspect of chimpanzee gestural sequences. Information about previous gestures reduced uncertainty in predicting subsequent gestures. The order of gestures within sequences appears to be less critical than their cooccurrence, challenging assumptions based on the linear patterning derived from vocal communication. The findings highlight the importance of methodological choices in sequence definition and suggest that chimpanzee gestural communication is characterised by a mix of predictability and flexibility, with implications for understanding the evolution of complex communication systems.

# 2 Information

The code provided below should enable researchers to replicate all results in this study. All functions are defined initially in this document, rather than standalone functions - use the Table of Content to navigate.

- 3 Set options
- 4 Set Libraries
- 5 Load Data

We have four datasets, each with a different time threshold for defining a sequence. We will load all datasets. They are consistently labelled as '\_5sec' (5 second time threshold), '\_rapid'

(based on rapid sequence definitions), '\_overlap' (overlapping sequences), and '\_solitary' (solitary gestures).

### 6 Markov transitions

#### 6.1 N-Grams

The following functions take the sequence objects, calculate the probabilities of elements transitioning into each other, and then bootstrap the data to check the stability of the conditional probabilities and their significance compared to random.

#### 6.2 Functions

#### 6.2.1 Calculate N-grams

This function will calculate the probabilities of AB, ABC, and ABCD.

#### 6.2.2 Bootstraps

This function bootstraps the n-grams to check for data quality.

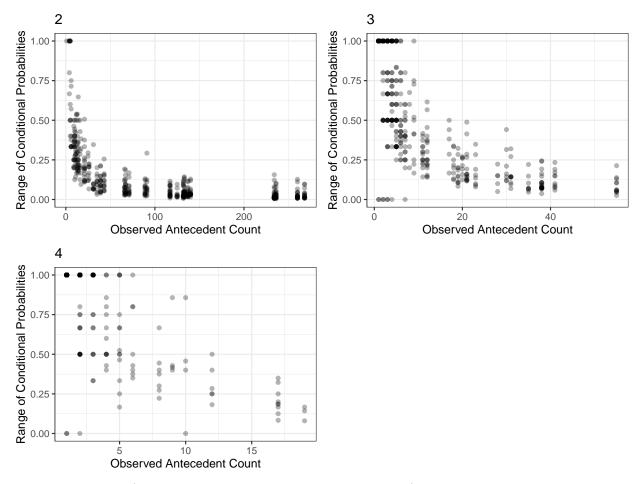
#### 6.2.3 Calculate 2,3, and 4-Grams

Here, we apply the n-gram function to the dataset.

## 6.3 Bootstrap N-grams

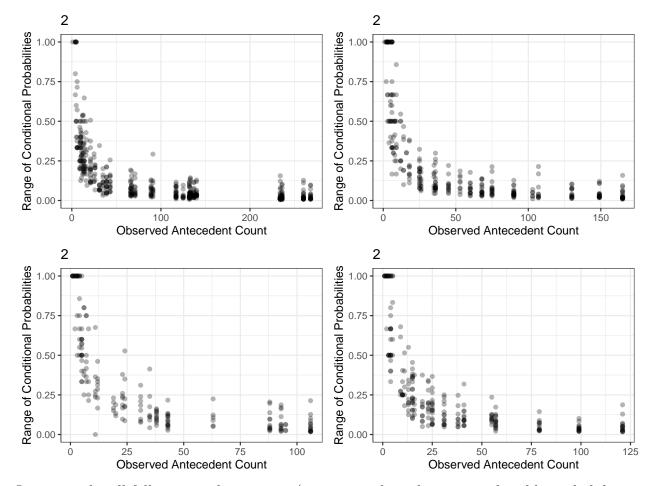
Here, we bootstrap the data and calculate the conditional probabilities to check how stable the conditional probabilities are. Set n to 1000

Now, we plot the distribution of the range of bootstrapped conditional probabilities, with the frequency of the consequent element on the x-axis and the probability range on the y-axis.



Even for 3-grams (two antecedents predicting third element) the conditional probabilities are highly unstable. We need to drop 4-grams, the conditional probabilities are all over the place.

Let's look at the different time intervals together.



Interestingly, all follow a similar pattern (rare antecedents have unpredictable probabilities, with increasing sample size there is increasing stability), but the inflection points occur at different sample sizes, indicating that, if we had the same sample size, maybe the different would not have similar stability. We can actually check that by testing the re-test reliability of each given different sample sizes.

# 7 Significant N-grams

We establish which gesture transitions are significant by randomising the gesture tokens, while keeping the gesture probability and the sequence lengths the same.

### 7.1 Functions

#### 7.1.1 Shuffle sequences for significance on different levels

Make a function to shuffle sequences while controlling sequence length.

### 7.1.2 Networks

## 7.2 Generate significance values

Here, we generate the significance values for the different time frames. We will use the bootstrapped data to check the significance of the observed conditional probabilities.

### 7.2.1 List significant ngrams

Make a list of the significant n-grams of all levels for the Full Sequences at 5 seconds. Change the time frame to see the significance there.

##		antecedent	consequent	count
##	1	StompObject,StompObject,StompObject	StompObject	5
##	2	<pre>HitObject,HitObject,HitObject</pre>	HitObject	6
##	3	Push, Push, Push	Push	7
##	4	HitOther, HitOther, HitOther	HitOther	5
##	5	Reach, Reach	Reach	10
##	6	Pull, Pull, Pull	Pull	17
##	7	<pre>HitObject,StompObject,HitObject</pre>	StompObject	6
##	8	${\tt BigLoudScratch,BigLoudScratch} \\$	${\tt BigLoudScratch}$	5
##	9	${\tt BigLoudScratch,BigLoudScratch}$	${\tt BigLoudScratch}$	21
##	10	<pre>HitObject,StompObject</pre>	StompObject	9
##	11	ObjectShake,ObjectShake	HitObject	8
##	12	HitObject,HitObject	HitObject	20
##	13	<pre>HitObject,StompObject</pre>	HitObject	11
##	14	ObjectShake,ObjectShake	ObjectMove	5
##	15	ObjectShake,ObjectShake	ObjectShake	23
##	16	ObjectShake,StompObject	ObjectShake	6
##	17	StompObject,StompObject	ObjectShake	5
##	18	StompObject,StompObject	StompObject	13
##	19	ObjectMove, ObjectMove	ObjectMove	5
##	20	HitObject,ObjectShake	ObjectShake	8
##	21	ObjectMove,ObjectShake	ObjectShake	5
##	22	StompObject,StompObject	HitObject	9
##	23	StompObject,HitObject	HitObject	11
##	24	ObjectShake,HitObject	ObjectShake	6
##		ObjectShake,ObjectShake	Jump	6
##		HitObject,HitObject	ObjectShake	5
##		HitObject,ObjectShake	HitObject	5
##	28	Push, Push	Push	16
##		StompObject,HitObject	StompObject	11
##		Fling, Fling	Fling	7
##		HitOther, HitOther	HitOther	12
##		Touch, Touch	Touch	13
##	33	HitObject,HitObject	StompObject	7

##	34	Reach, Reach	Reach	26
	35	Pull, Pull	Pull	24
##		Grab, Grab	Grab	5
	37	Present, BigLoudScratch	BigLoudScratch	6
##	38	BigLoudScratch, Present	BigLoudScratch	16
	39	BigLoudScratch,BigLoudScratch	Present	9
##	40	BigLoudScratch	BigLoudScratch	122
##	41	Present	BigLoudScratch	107
##	42	ObjectMove	ObjectMove	33
##	43	Stroke	Stroke	7
##	44	Embrace	Bite	16
##	45	Push	Push	49
##	46	HitObject	StompObject	52
##	47	StompObject	StompObject	70
##	48	ObjectMove	StompObject	16
##	49	ObjectShake	ObjectShake	122
##	50	ObjectShake	${ t HitObject}$	29
##	51	HitObject	ObjectMove	11
##	52	Reach	Reach	89
##	53	Reach	Touch	16
##	54	Swing	${ t HitObject}$	9
##	55	HitObject	${ t HitObject}$	77
##	56	${ t BigLoudScratch}$	Present	84
##	57	Touch	Touch	63
##	58	StompObject	HitObject	64
##	59	${ t BigLoudScratch}$	Pull	8
##	60	Shake	Shake	8
##	61	Pull	Pull	40
	62	HitObject	Jump	9
	63	Jump	HitObject	7
	64	HitObject	Swing	9
	65	Swing	HitOther	11
	66	ObjectShake	ObjectMove	20
	67	Rocking	ObjectShake	5
	68	ObjectShake	Rocking	6
	69	ObjectMove	ObjectShake	24
	70	ObjectShake	Jump	8
	71	Jump	ObjectShake	6
	72	Push	Touch	15
	73	StompObject	ObjectMove	14
	74	ObjectMove	HitObject	16
	75	Touch	Reach	7
	76 77	HitObject	HitOther	9
	77	StompObject	Swing	12
##	78	Fling	Fling	21

##	79	StompObject	ObjectShake	19
##	80	ObjectShake	StompObject	35
##	81	Dangle	Swing	28
##	82	Bite	HitOther	6
	83	Touch	GrabHold	7
##	84	Grab	Bite	18
	85	StompObject	Dangle	10
##	86	Swing	Shake	5
##	87	GrabHold	Bite	18
	88	Swing	Dangle	13
##	89	Shake	Swing	5
##	90	HitOther	Grab	12
##	91	Grab	Grab	21
##	92	GrabHold	Grab	7
	93	ObjectMove	Swing	9
##	94	Swing	Swing	24
##	95	Swing	ObjectMove	9
##	96	ObjectMove	Shake	5
##	97	ObjectMove	ThrowObject	5
##	98	HitObject	ObjectShake	33
##	99	Swing	ObjectShake	12
	100	Swing	StompObject	10
	101	ObjectShake	Swing	15
	102	StompObject	HitOther	7
	103	StompObject	HeadStand	5
##	104	Dangle	HitObject	13
##	105	HitObject	Dangle	5
##	106	Dangle	StompObject	5
##	107	Bite	Bite	10
##	108	PresentGenitals	PresentGenitals	9
##	109	Touch	Push	9
##	110	Grab	HitOther	7
##	111	HitOther	HitOther	52
##	112	Pull	Push	7
##	113	HitObject	Reach	5
##	114	Raise	Touch	6
##	115	Reach	Raise	6
##	116	Raise	Reach	6
##	117	Raise	Raise	10
##	118	Dangle	Dangle	6
##	119	Grab	Touch	7
	120	Touch	Bite	8
##	121	Touch	HitOther	5
##	122	LeafClip	LeafClip	10
	123	Dangle	HitOther	13
		J		

##	124			HitOther		Swing	8
	125			Grab		GrabHold	6
	126			HitOther		Dangle	5
	127			Dangle		Grab	5
	128			LeafClip	Ob-	jectShake	5
	129			HitOther	0.0	GrabHold	5
##	130			HitOther	St	tompOther	8
	131			Touch	~	Grab	5
	132			Raise	Sto	ompObject	5
	133			Pull		Touch	5
	134			Raise	BigLoı	ıdScratch	23
	135		I	HitObject	•	ıdScratch	6
	136			Touch	6	Raise	7
	137		BigLou	ıdScratch		Raise	14
	138		•	ıdScratch		Push	14
	139		•	ıdScratch	Present		5
	140		O	Push		Raise	6
##		conditional_probability	specificity	expected	pvalue	level	
##	1		0.09259259	0	0	4	
##	2	0.50000000	0.09375000	0	0	4	
##	3	0.7000000	0.30434783	0	0	4	
##	4	0.83333333	0.17857143	0	0	4	
##	5	1.00000000	0.50000000	0	0	4	
##	6	0.89473684	0.54838710	0	0	4	
##	7	0.6666667	0.11111111	0	0	4	
##	8	0.62500000	0.31250000	0	0	4	
##	9	0.55263158	0.31343284	0	0	3	
##	10	0.29032258	0.08653846	0	0	3	
##	11	0.14545455	0.06250000	0	0	3	
##	12	0.48780488	0.15625000	0	0	3	
##	13	0.35483871	0.08593750	0	0	3	
##		0.09090909	0.10000000	0	0	3	
	15	0.41818182	0.19658120	0	0	3	
	16	0.35294118	0.05128205	0	0	3	
##		0.13157895	0.04273504	0	0	3	
	18	0.34210526	0.12500000	0	0	3	
##		0.26315789	0.10000000	0	0	3	
##		0.4444444	0.06837607	0	0	3	
	21	0.41666667	0.04273504	0	0	3	
##		0.23684211	0.07031250	0	0	3	
##		0.36666667	0.08593750	0	0	3	
##		0.30000000	0.05128205	0	0	3	
##		0.10909091	0.25000000	0	0	3	
	26	0.12195122	0.04273504	0	0	3	
##	21	0.2777778	0.03906250	0	0	3	

##	28	0.76190476	0.34042553	0	0	3
##	29	0.3666667	0.10576923	0	0	3
##	30	1.00000000	0.50000000	0	0	3
##	31	0.57142857	0.2222222	0	0	3
##	32	0.56521739	0.34210526	0	0	3
##	33	0.17073171	0.06730769	0	0	3
##	34	0.74285714	0.57777778	0	0	3
##	35	0.85714286	0.52173913	0	0	3
##	36	0.5555556	0.19230769	0	0	3
##	37	0.6666667	0.08955224	0	0	3
##	38	0.8888889	0.23880597	0	0	3
##	39	0.23684211	0.52941176	0	0	3
##	40	0.45522388	0.43262411	0	0	2
##	41	0.85600000	0.37943262	0	0	2
##	42	0.25000000	0.31428571	0	0	2
##	43	0.50000000	0.3888889	0	0	2
##	44	0.64000000	0.18390805	0	0	2
##	45	0.53846154	0.48039216	0	0	2
##	46	0.22033898	0.23529412	0	0	2
##	47	0.29914530	0.31674208	0	0	2
##	48	0.12121212	0.07239819	0	0	2
##	49	0.46923077	0.49593496	0	0	2
##	50	0.11153846	0.11836735	0	0	2
##	51	0.04661017	0.10476190	0	0	2
##	52	0.63571429	0.69531250	0	0	2
##	53	0.11428571	0.11034483	0	0	2
##	54	0.07692308	0.03673469	0	0	2
##	55	0.32627119	0.31428571	0	0	2
##	56	0.31343284	0.85714286	0	0	2
##	57	0.45985401	0.43448276	0	0	2
##	58	0.27350427	0.26122449	0	0	2
##	59	0.02985075	0.10666667	0	0	2
##	60	0.20512821	0.21621622	0	0	2
##	61	0.60606061	0.53333333	0	0	2
##	62	0.03813559	0.31034483	0	0	2
##	63	0.26923077	0.02857143	0	0	2
##	64	0.03813559	0.06766917	0	0	2
##	65	0.09401709	0.07857143	0	0	2
##	66	0.07692308	0.19047619	0	0	2
##	67	0.35714286	0.02032520	0	0	2
##	68	0.02307692	0.37500000	0	0	2
##	69	0.18181818	0.09756098	0	0	2
##	70	0.03076923	0.27586207	0	0	2
##	71	0.23076923	0.02439024	0	0	2
##	72	0.16483516	0.10344828	0	0	2

##	73	0.05982906	0.13333333	0	0	2
##	74	0.12121212	0.06530612	0	0	2
##	75	0.05109489	0.05468750	0	0	2
##	76	0.03813559	0.06428571	0	0	2
##	77	0.05128205	0.09022556	0	0	2
##	78	0.67741935	0.60000000	0	0	2
##	79	0.08119658	0.07723577	0	0	2
##	80	0.13461538	0.15837104	0	0	2
##	81	0.31460674	0.21052632	0	0	2
##	82	0.17142857	0.04285714	0	0	2
##	83	0.05109489	0.17948718	0	0	2
##	84	0.25352113	0.20689655	0	0	2
##	85	0.04273504	0.18181818	0	0	2
##	86	0.04273504	0.13513514	0	0	2
##	87	0.41860465	0.20689655	0	0	2
##	88	0.11111111	0.23636364	0	0	2
##	89	0.12820513	0.03759398	0	0	2
##	90	0.09022556	0.17647059	0	0	2
##	91	0.29577465	0.30882353	0	0	2
##	92	0.16279070	0.10294118	0	0	2
##	93	0.06818182	0.06766917	0	0	2
##	94	0.20512821	0.18045113	0	0	2
##	95	0.07692308	0.08571429	0	0	2
##	96	0.03787879	0.13513514	0	0	2
##	97	0.03787879	0.50000000	0	0	2
##	98	0.13983051	0.13414634	0	0	2
##	99	0.10256410	0.04878049	0	0	2
##	100	0.08547009	0.04524887	0	0	2
##	101	0.05769231	0.11278195	0	0	2
##	102	0.02991453	0.05000000	0	0	2
##	103	0.02136752	0.41666667	0	0	2
##	104	0.14606742	0.05306122	0	0	2
##	105	0.02118644	0.09090909	0	0	2
##	106	0.05617978	0.02262443	0	0	2
##	107	0.28571429	0.11494253	0	0	2
##	108	0.42857143	0.33333333	0	0	2
##	109	0.06569343	0.08823529	0	0	2
##	110	0.09859155	0.05000000	0	0	2
##	111	0.39097744	0.37142857	0	0	2
##	112	0.10606061	0.06862745	0	0	2
##	113	0.02118644	0.03906250	0	0	2
##	114	0.08955224	0.04137931	0	0	2
##	115	0.04285714	0.08695652	0	0	2
##	116	0.08955224	0.04687500	0	0	2
##	117	0.14925373	0.14492754	0	0	2

##	118	0.06741573	0.10909091	0	0	2
##	119	0.09859155	0.04827586	0	0	2
##	120	0.05839416	0.09195402	0	0	2
##	121	0.03649635	0.03571429	0	0	2
##	122	0.58823529	0.76923077	0	0	2
##	123	0.14606742	0.09285714	0	0	2
##	124	0.06015038	0.06015038	0	0	2
##	125	0.08450704	0.15384615	0	0	2
##	126	0.03759398	0.09090909	0	0	2
##	127	0.05617978	0.07352941	0	0	2
##	128	0.29411765	0.02032520	0	0	2
##	129	0.03759398	0.12820513	0	0	2
##	130	0.06015038	0.38095238	0	0	2
##	131	0.03649635	0.07352941	0	0	2
##	132	0.07462687	0.02262443	0	0	2
##	133	0.07575758	0.03448276	0	0	2
##	134	0.34328358	0.08156028	0	0	2
##	135	0.02542373	0.02127660	0	0	2
##	136	0.05109489	0.10144928	0	0	2
##	137	0.05223881	0.20289855	0	0	2
##	138	0.05223881	0.13725490	0	0	2
##	139	0.01865672	0.18518519	0	0	2
##	140	0.06593407	0.08695652	0	0	2

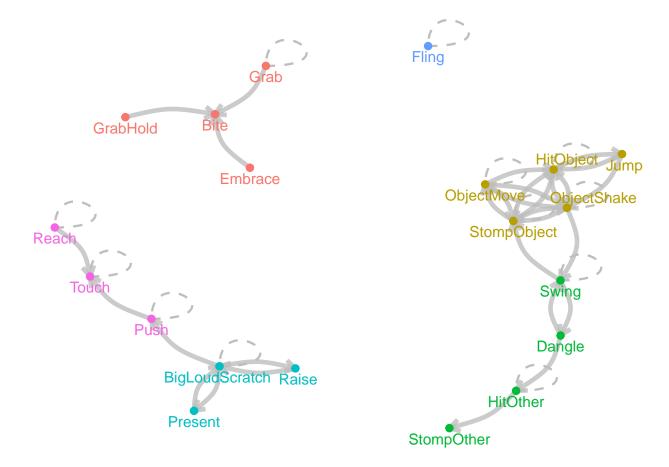
## 7.2.2 Make list of ngrams that are significant across time frames

Here is the table with the shared transitions across all time frames.

antecedent	consequent
BigLoudScratch	BigLoudScratch
Present	BigLoudScratch
BigLoudScratch	Present
ObjectMove	ObjectMove
ObjectShake	ObjectMove
BigLoudScratch	Push
HitObject	HitObject
StompObject	HitObject
StompObject	StompObject
HitOther	HitOther
ObjectShake	ObjectShake
Swing	Swing
Dangle	Swing
Touch	Touch
BigLoudScratch	Raise

Here is what the network of only the shared transitions looks like - we use 3 shared instead of 4 to be less conservative.

### **Concurrence Transition Network**



### 7.3 Networks

## overlap



# response\_waiting



### 1sec

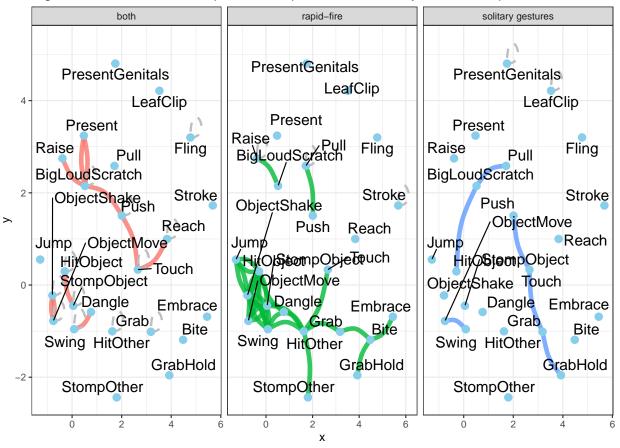


### 5sec



### 7.3.1 Rapid response vs solitary gesture network

Significant Transitions For Rapid-Fire Sequences and Solitary Gesture Sequences



Rapid fire sequences are focused on object-related and contact gestures (stomping, hitting, biting, embracing) while the ones that definitely need response waiting are often those that cannot be physically done too quickly together or those that in a rapid-fire sequence would not be marked as distinct (without response waiting, there would be no way to tease apart Grab, GrabHold, Touch, and Push).

# 8 Significant 2-gram orders

Let's check if there are any combinations where the direction matters (conditional probability of B following A being more likely than expected by random distribution of elements within sequences). We shuffle elements within sequences while keeping sequence lengths the same. We do this for the 5sec full sequences for now.

#### 8.1 Functions

## 8.2 Generate significance values

Make a list of the significant n-grams.

antecedent	consequent	count	conditional_probability	$expected\_within$	improvement
Embrace	Bite	16	0.6400000	0.3416952	0.2983048
GrabHold	Bite	18	0.4186047	0.2301305	0.1884742
Grab	Bite	18	0.2535211	0.1246205	0.1289006
Jump	HitObject	7	0.2692308	0.1733109	0.0959198
Bite	HitOther	6	0.1714286	0.0947642	0.0766643
Raise	BigLoudScratch	23	0.3432836	0.2710566	0.0722270
Push	Touch	15	0.1648352	0.1112090	0.0536262
Swing	HitOther	11	0.0940171	0.0570022	0.0370149
Raise	StompObject	5	0.0746269	0.0376200	0.0370068
ObjectShake	StompObject	35	0.1346154	0.1025986	0.0320168
HitOther	StompOther	8	0.0601504	0.0347647	0.0253857
StompObject	HitObject	64	0.2735043	0.2507648	0.0227394
Push	Raise	6	0.0659341	0.0436033	0.0223308
HitObject	Jump	9	0.0381356	0.0165373	0.0215983
Touch	HitOther	5	0.0364964	0.0190859	0.0174104
StompObject	Dangle	10	0.0427350	0.0270353	0.0156998
Touch	GrabHold	7	0.0510949	0.0358942	0.0152007
ObjectShake	Swing	15	0.0576923	0.0429345	0.0147578
BigLoudScratch	Push	14	0.0522388	0.0375138	0.0147250
StompObject	HeadStand	5	0.0213675	0.0071485	0.0142190
${\bf BigLoudScratch}$	Pull	8	0.0298507	0.0204471	0.0094037

It mainly seems like physical contact (Bite, Pull, Push, Touch) usually follows rather than precedes other gestures.

# 9 Entropy

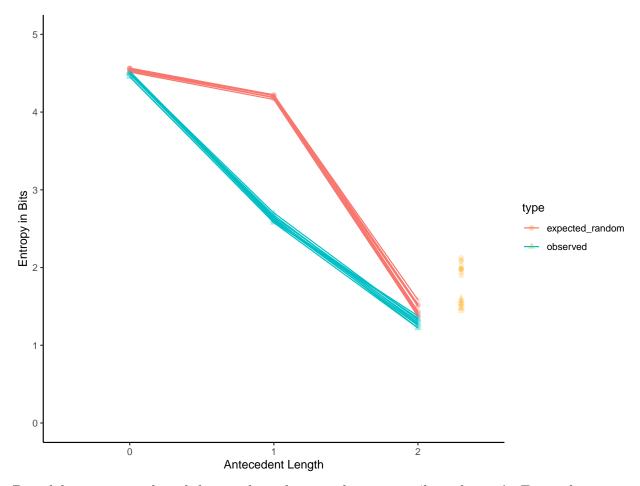
### 9.1 Functions

### 9.1.1 Calculate Entropy

This function calculates the entropy of a given sequence.

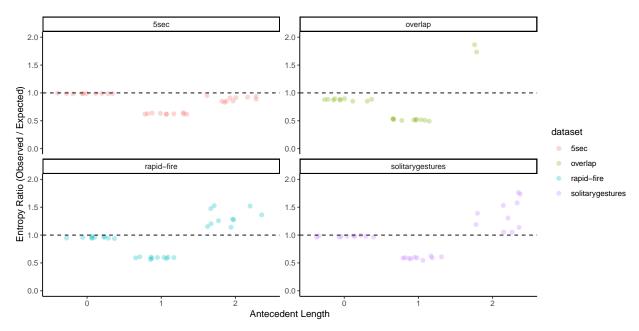
## 9.2 Entropies all datasets

Calculate the entropies across all 5 datasets. Let's plot this.



Doted lines are predicted for random, lower values mean 'less chaotic'. From the entropies, there is considerable improvement in predictability moving from no antecedent to one antecedent, but not from 1 antecedent to 2 antecedents. There seems a slight improvement of having 2 antecedent when the order is removed ('alphabetical'), indicating the order just adds noise.

Let's plot the ratio between expected and observed entropies. Anything closer to 1 or above means randomness, anything closer to 0 means more predictability.

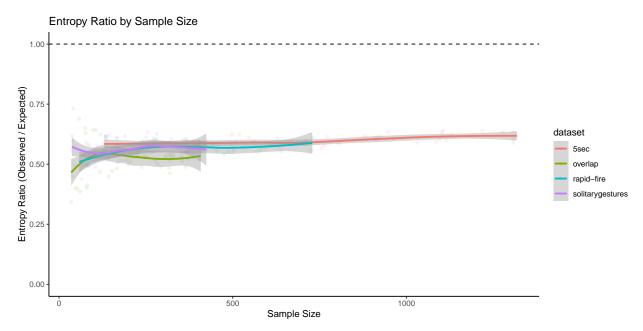


For level 0 and 1 (base probabilities and 1-element antecedents), the different sequence types are the same apart from the Overlap sequences, which are more predictable at Level 1 (which mirrors our results above, there are simply fewer options). For 2-antecedent transitions, the 5-second sequence definition adds the most predictability about what happens next; in 1-second sequences and overlap, there is no added information above random (most of them aren't even visible in this chart); the solitary gesture (which should be fairly similar anyways) add a bit of information, but on average less than the 5sec sequences.

### 9.2.1 Impact of sample size on entropies

The different datasets have different sample sizes. Let's check how the sample size impacts the entropy.

For the first level entropy, this looks like this: essentially, all datasets have sufficient data to accurately calculate the entropy inherent in the first order transitions, and they do not differ a lot (apart from overlap potentially having less entropy compared to predicted). The y-axis is the ratio between the observed and expected entropy values.



We make a table of the different expected and observed entropies for the full dataset for each:

dataset	level	order	entropy	expected_entropy	entropy_ratio
5sec	1	observed	2.435090	3.951228	0.6162869
overlap	1	observed	1.727917	3.296614	0.5241491
rapid-fire	1	observed	2.152752	3.678078	0.5852926
solitarygestures	1	observed	1.834860	3.252357	0.5641632

# 10 Prediction Models

### 10.1 Functions

### 10.1.1 Comparison of predictability of different datasets

```
## [1] 1.0 0.4

## [1] 1.0 0.6

## [1] 1.0 0.8

## [1] 1 1

## [1] 1.0 0.4

## [1] 1.0 0.6

## [1] 1 1

## [1] 1.0 0.4

## [1] 1.0 0.6

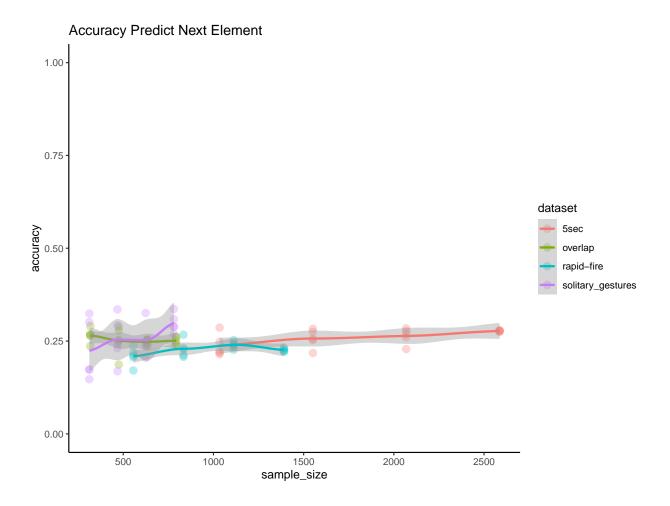
## [1] 1.0 0.6

## [1] 1.0 0.6
```

## [1] 1 1

- ## [1] 1.0 0.4
- ## [1] 1.0 0.6
- ## [1] 1.0 0.8
- ## [1] 1 1
- ## [1] 1.0 0.4
- ## [1] 1.0 0.6
- ## [1] 1.0 0.8
- ## [1] 1 1
- ## [1] 2.0 0.4
- ## [1] 2.0 0.6
- ## [1] 2.0 0.8
- ## [1] 2 1
- ## [1] 2.0 0.4
- ## [1] 2.0 0.6
- ## [1] 2.0 0.8
- ## [1] 2 1
- ## [1] 2.0 0.4
- ## [1] 2.0 0.6
- ## [1] 2.0 0.8
- ## [1] 2 1
- ## [1] 2.0 0.4
- ## [1] 2.0 0.6
- ## [1] 2.0 0.8
- ## [1] 2 1
- ## [1] 2.0 0.4
- ## [1] 2.0 0.6
- ## [1] 2.0 0.8
- ## [1] 2 1
- ## [1] 3.0 0.4
- ## [1] 3.0 0.6
- ## [1] 3.0 0.8
- ## [1] 3 1
- ## [1] 3.0 0.4
- ## [1] 3.0 0.6
- ## [1] 3.0 0.8
- ## [1] 3 1
- ## [1] 3.0 0.4
- ## [1] 3.0 0.6
- ## [1] 3.0 0.8
- ## [1] 3 1
- ## [1] 3.0 0.4
- ## [1] 3.0 0.6
- ## [1] 3.0 0.8
- ## [1] 3 1
- ## [1] 3.0 0.4

- ## [1] 3.0 0.6
- ## [1] 3.0 0.8
- ## [1] 3 1
- ## [1] 4.0 0.4
- ## [1] 4.0 0.6
- ## [1] 4.0 0.8
- ## [1] 4 1
- ## [1] 4.0 0.4
- ## [1] 4.0 0.6
- ## [1] 4.0 0.8
- ## [1] 4 1
- ## [1] 4.0 0.4
- ## [1] 4.0 0.6
- ## [1] 4.0 0.8
- ## [1] 4 1
- ## [1] 4.0 0.4
- ## [1] 4.0 0.6
- ## [1] 4.0 0.8
- ## [1] 4 1
- ## [1] 4.0 0.4
- ## [1] 4.0 0.6
- ## [1] 4.0 0.8
- ## [1] 4 1



## 10.2 Higher-order predictions

#### 10.2.1 Data preparation

Let's check how predictable transitions are on different levels. We use Naive Bayes classifier (which is agnostic to sequence information) and Random Forests to predict the next element based on the previous one. Originally, this also involved LSTM, but Long-Short Term Memory deep learning (which represents sequence information), but the overfitting was so extreme that it is hard to interpret the results. We look at 3-grams: AB predicting C. We check whether A alone (one gesture removed), B alone (previous gesture), AB together, or a alphabetisation of AB best predicts the next element.

#### 10.2.2 Sequence Prediction