

#### **COGNITIVE CONTROL IN MEDIA MULTITASKERS**

Xiaoying Gao 12.01.2015

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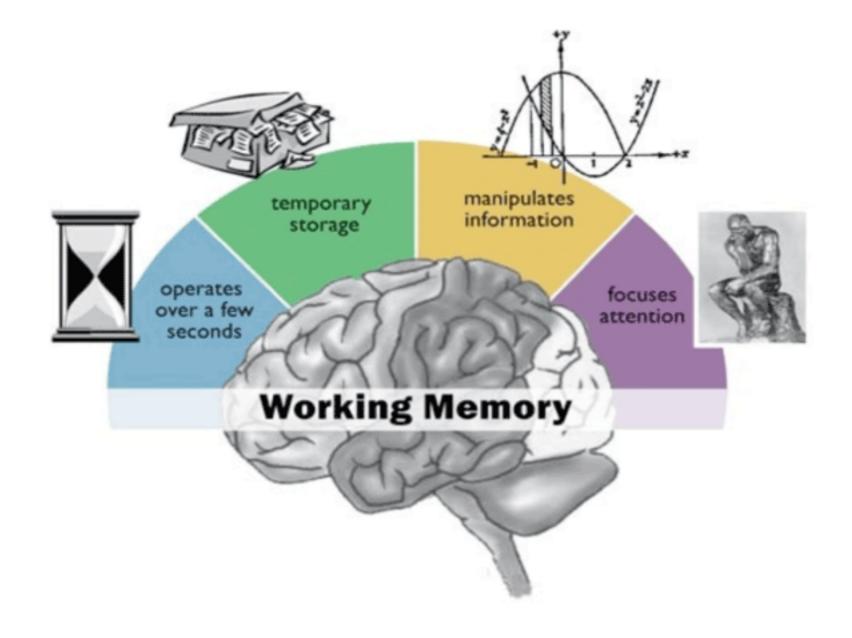
## **LEARNING GOALS**

Learn the relationship between chronic media multitasking and cognitive control abilities

- ability of filtering environment distractions
- ability of filtering irrelevant representations in memory

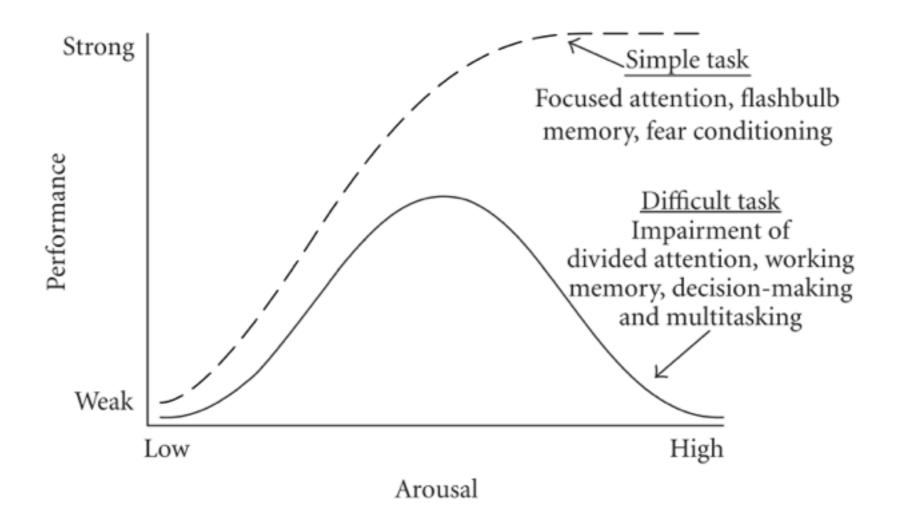
#### WHAT IS WORKING MEMORY?

Working memory consists of the brain processes used for temporary storage and manipulation of information.



#### YERKES-DODSON LAW

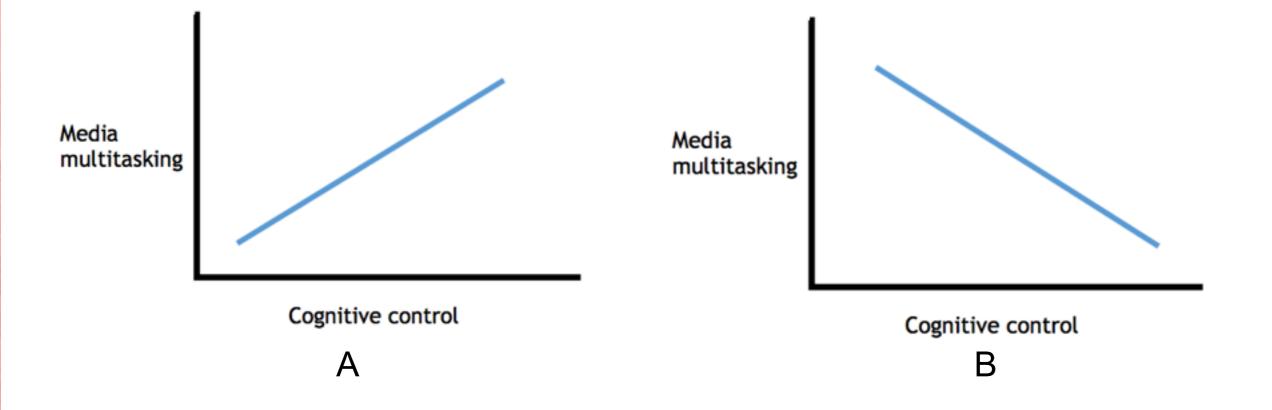
Research has found that different tasks require different levels of arousal for optimal performance



## **MULTITASKERS**

Relationship between chronic media multitasking and cognitive abilities?

Two hypothetical cases:





For Media multitaskers, When can irrelevant stimuli have positive or negative effects on working performance? Please give some examples.

(group of 2-3 students in 2mins)

#### HMMs vs. LMMs

#### Heavy vs. Light media multitaskers

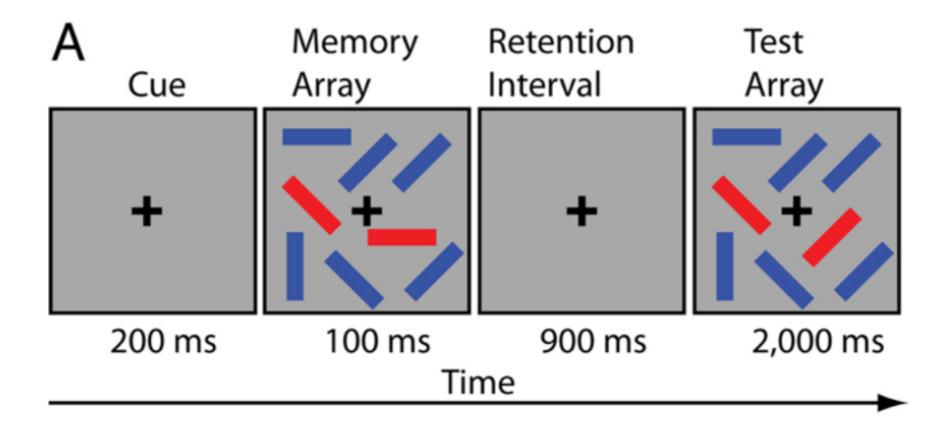
MMI is created by computing a sum across primary media use weighted by the percentage of time spent with each primary medium.

$$\mathbf{MMI} = \sum_{i=1}^{11} \frac{m_i \times h_i}{h_{\text{total}}}$$

HMMs: greater than one standard deviation above the mean LMMs: less than one standard deviation below the mean

#### • Filtering Task

indicate whether or not a target (red) rectangle had changed orientation from the first exposure to the second



Filtering Task

Results:

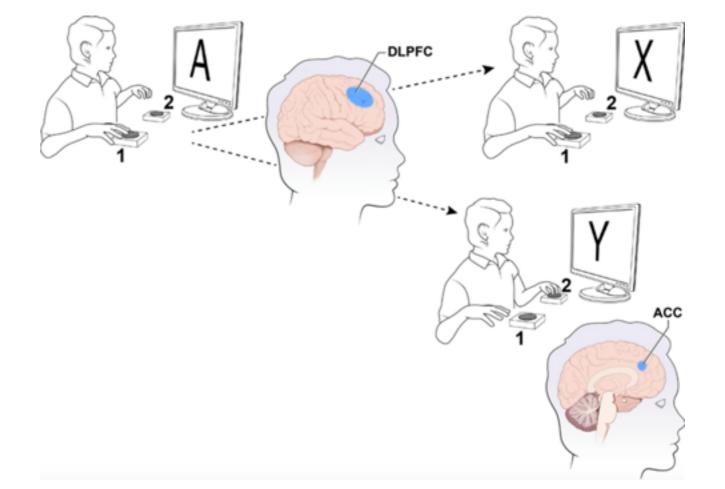
- 1. HMMs were affected by distractors
- LMMs have the ability to successfully filter out irrelevant stimuli

1.8

В

#### AX-CPT Tasks

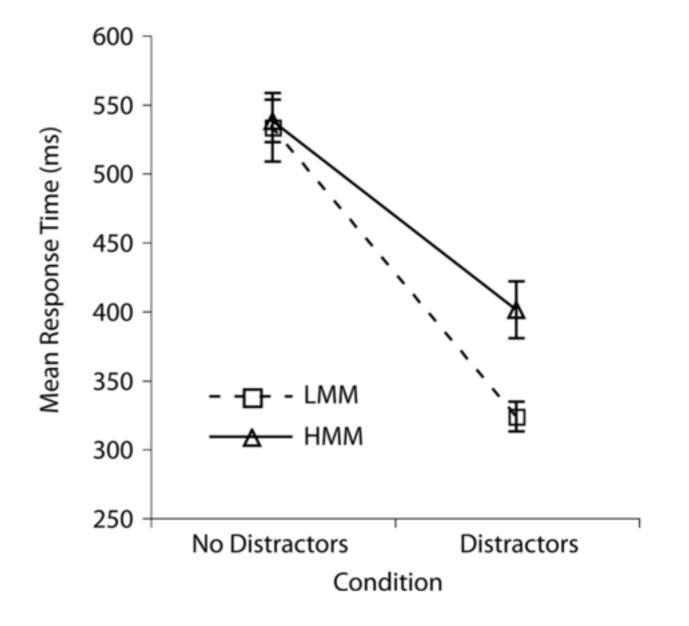




AX-CPT Tasks

#### Results:

 HMMs are less selective in allowing information into working memory, and are therefore more affected by distractors



#### Task-switching

Participants switched back and forth between classifying numbers and classifying letters, according to a cue presented at the outset of each trial

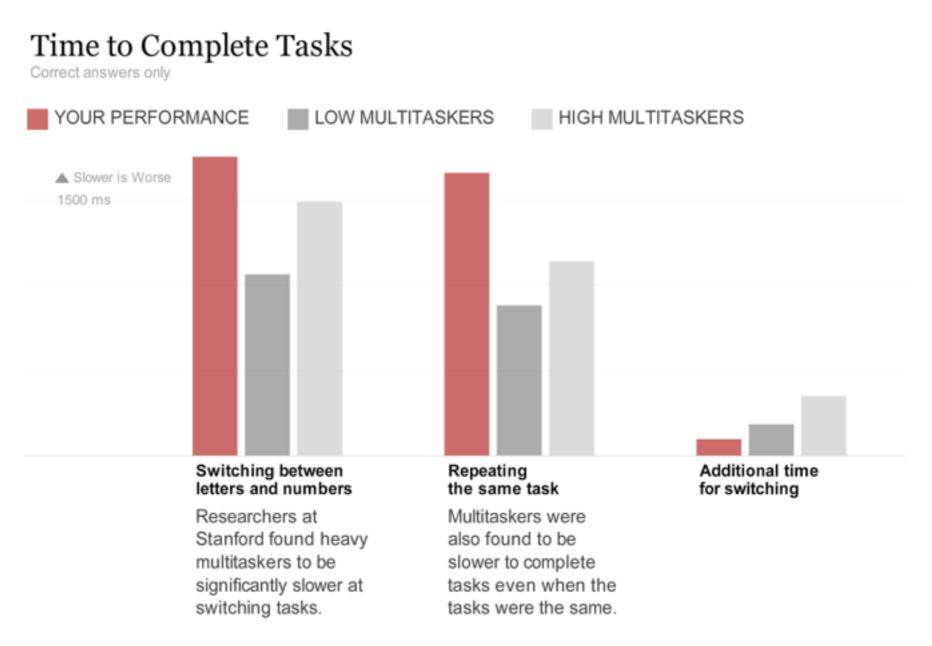
## NUMBER





#### Task-switching

HMMs are less capable of filtering out the irrelevant task-set representation in memory on a given trial





Please explain why response time to switch trials is longer than that to nonswitch trials? Do you have some solutions for improving the efficiency of task-switching?

group of 2-3 students in 2mins

#### • Two- and three-back task

Participants are presented a series of individual letters, filled by a white screen. Indicate whether or not the present letter is a "target".

> this appeared one before the last, so click the hit box (during the actual game, it will not stop!)

last items:





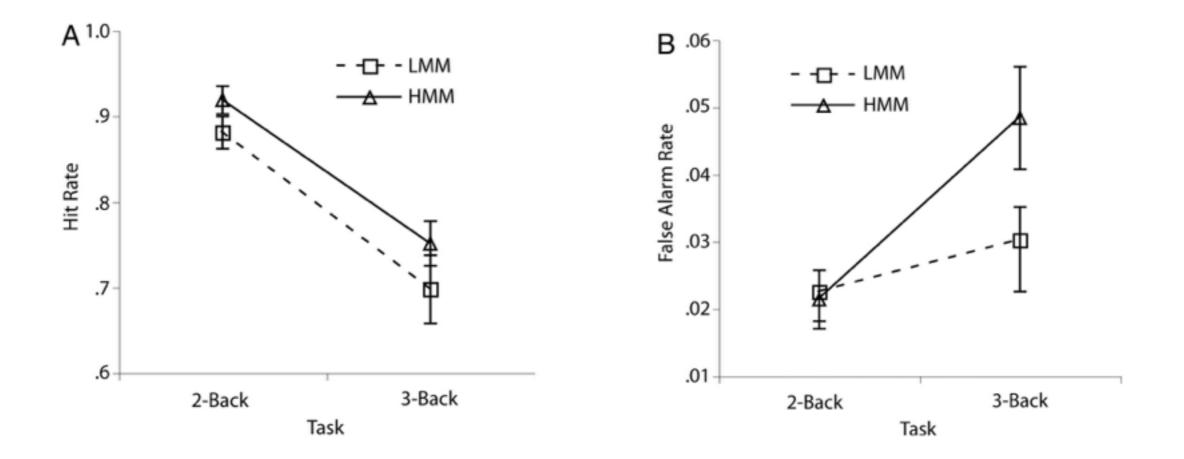
0-back (current)



#### • Two- and three-back task

**Results:** 

HMMs are less capable of filtering out irrelevant representations in memory.



## **DISCUSSION 3**

Some brilliant ideas are created in just a few seconds, so we can see that working memory may have an important role in creativity. If HMMs are less capable of filtering out irrelevant representation in memory, will they become less creative?

group of 2-3 students in 2mins

## COMMENTARY

One possible flaw in the methodology is considering instant messaging as a primary medium while not considering text messaging as a primary medium. The paper reasons that the reason for this was because text messaging could not be accurately described by hours of use. — Jeremy

I am also thinking that there might be differences between different age groups. Testing on middle-age people might have a different result than testing on teenagers. One reason I can think of is that teenagers are actually easier to get distracted compare to elders. — Chen

it's more important to apply information cognition to higher level ordering as opposed to details because we have become accustomed to the ease of accessing those details through processing aids. If all this is true, what's next after multitasking as aided processing through computers becomes stronger and stronger? — Jesse



# Examining the robustness of sensor-based statistical models of human interruptibility

Xiaoying Gao 12.01.2015

## **LEARNING GOALS**

#### Learn the sensor-based statistical models

sensors

Bayes classifier

wrapper-based feature selection

 Learn how to measure the situation that the office workers would like to be uninterrupted.

## **DATA COLLECTION**

- Self-reports:
- USB microphone:
- USB sensor board:

two magnetic switches: door two motion sensor: motion a magnetic switch: phone

software:

the number of keyboard, mouse move, and mouse click

## **DISCUSSION 1**

If you are a designer and want to detect in what situation would a software engineer be non-interruptible in the office, what kinds of situation would you like to concern? and design a sensor to detect it.

group of 2-3 students in 2mins

## **NAÏVE BAYES CLASSIFIER**

$$\begin{split} p(C|F_1, \dots, F_n) & \text{ What we want} \\ p(C|F_1, \dots, F_n) &= \frac{p(C) \ p(F_1, \dots, F_n | C)}{p(F_1, \dots, F_n)} & \text{Bayes} \\ p(C) \ p(F_1, \dots, F_n | C) &= \ p(C, F_1, \dots, F_n) \\ p(C, F_1, \dots, F_n) &= p(C) \ p(F_1, \dots, F_n | C) \\ &= \ p(C) \ p(F_1 | C) \ p(F_2, \dots, F_n | C, F_1) \\ &= \ p(C) \ p(F_1 | C) \ p(F_2 | C, F_1) \ p(F_3, \dots, F_n | C, F_1, F_2) \\ &= \ p(C) \ p(F_1 | C) \ p(F_2 | C, F_1) \ \dots \ p(F_n | C, F_1, F_2, F_3, \dots, F_{n-1}) \end{split}$$
Naively assume

 $p(F_i|C, F_j) = p(F_i|C),$   $p(F_i|C, F_j, F_k) = p(F_i|C),$   $p(F_i|C, F_j, F_k, F_l) = p(F_i|C),$  $p(C|F_1, \dots, F_n) = \frac{1}{Z}p(C)\prod_{i=1}^n p(F_i|C),$ 

Assume types of distributions and parameterize from training data

Demo: <u>https://www.youtube.com/watch?v=fo-M2OIQoD4</u>

## **NAÏVE BAYES CLASSIFIER**

Strengths and weaknesses of algorithm

- Easy to understand, implement: Decides simply based on class that provides highest probability
- Highly scalable
- Assumes independent features, which may not always be the case
- Only 'attends' to features provided, dependent on features provided, supervised

#### **WRAPPER-BASED FEATURE SELECTION**

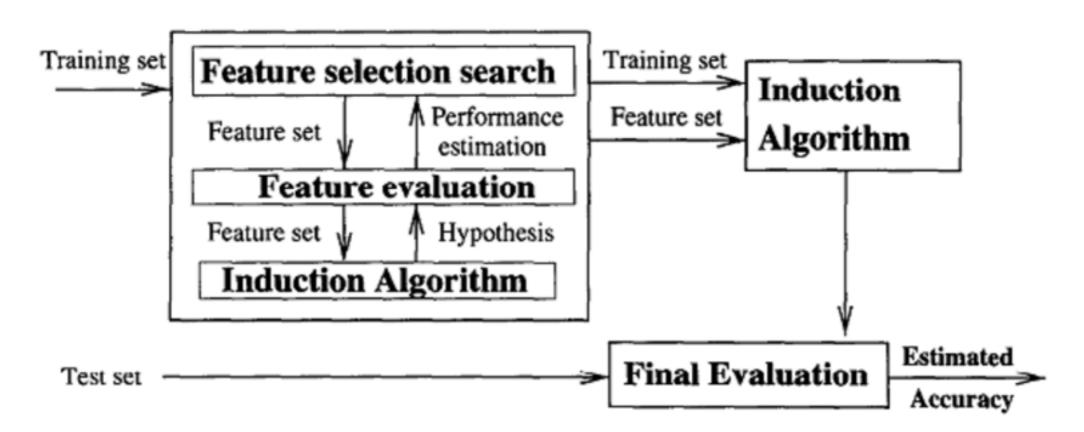


Fig. 1. The wrapper approach to feature subset selection. The induction algorithm is used as a "black box" by the subset selection algorithm.

#### **WRAPPER-BASED FEATURE SELECTION**

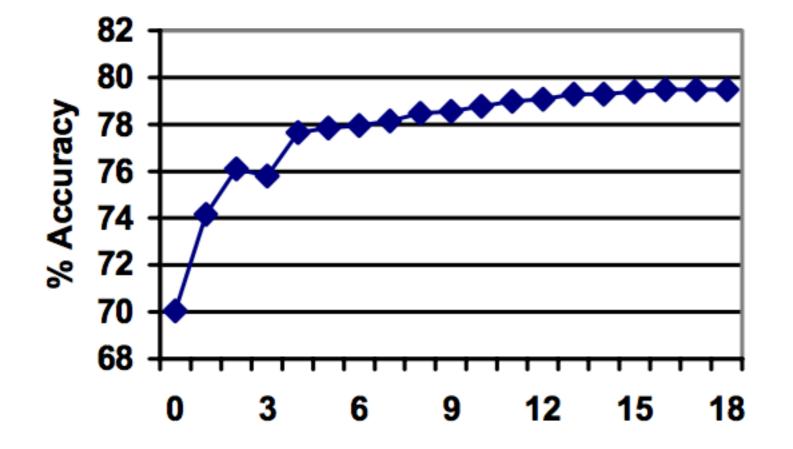


Figure 3. Number of features versus percent accuracy.

## **DISCUSSION 2**

Please select three main features which will most represent a manager or a researcher is non-interruptible in the office. What's the reason for your selection? (group of 2-3 students in 2mins)

features:

- 1. whether the phone is off its hook
- 2. whether the door is open, cracked, or closed
- 3. whether the talking detector has detected
- 4. whether the motion detectors has been triggered 60 times
- 5. whether the subject had generated 60 mouse move
- 6. the number of keyboard input
- 7. the number of mouse click

#### WRAPPER-BASED FEATURE SELECTION

#### Manager Data:

- whether the phone was off its hook in the last 15 seconds.
- 30 mouse move events in the last 15 seconds
- whether talking had been detected for 3 of the last 5 mins

#### **Researcher Data:**

- whether talking had been detected for 30 of the last seconds
- 60 mouse move events inside VS in the last 30 seconds
- whether typed 60 characters in the last 15 seconds

#### **Intern Data:**

- mouse activity in a window created by java.exe
- whether motion detectors triggered 60 times in the last 30 mins
- whether talking had been detected for 30 of the last seconds

#### **MODEL PERFORMANCE**

		Highly	Highly			
-44	Catagory	Interrup		Non-Inter		
#	Category	1	2	3	4	5
1	Manager	17	31	10	19	37
2	Manager	2	8	36	26	26
3	Researcher	67	7	8	13	10
4	Researcher	23	16	27	3	34
5	Researcher	4	7	24	18	51
6	Researcher	5	34	29	12	27
7	Researcher	0	6	12	16	34
8	Intern	26	28	25	11	13
9	Intern	3	17	12	15	17
10	Intern	11	28	2	25	43

Total .	158	182	185	158	292
10121   1	6.2%	18.7%	19.0%	16.2%	292 29.9%

Figure 1. Distribution of interruptibility self-reports.

		Model		
		Other Values	Highly Non	
teport	Other Values	640 65.6%	43 4.4%	
Self-Report	Highly Non	157 16.1%	135 13.8%	
		Accuracy: 79.5% Base: 70.1%		

Figure 2. Performance of model built from all collected data.

## **SENSOR COMBINATIONS**

	No Microphone Manager Data Model			No Microphone Researcher Data Model			No Microphone Intern Data Model		
	Other Values	Highly Non		Other Values	Highly Non		Other Values	Highly Non	
	145 68.4%	4 1.9%		314 61.6%	17 6.4%		200 72.5%	3 1.1%	
	35 16.5%	28 13.2%		86 12.5%	70 19.5%		52 18.8%	21 7.6%	
	Accuracy: 81.6% Base: 70.		Accuracy: 78.9% Base: 68.			Accuracy: 80.1% Base: 73.6			
Acc	Accuracy: 87.7%			81.8%			80.1%		



# Thanks!

Xiaoying Gao 12.01.2015