Decoding Human Texture Perception with Interpretable Machine Learning

Li Zou & Yasemin Vardar

Haptic Interface Technology Lab
Department of Cognitive Robotics

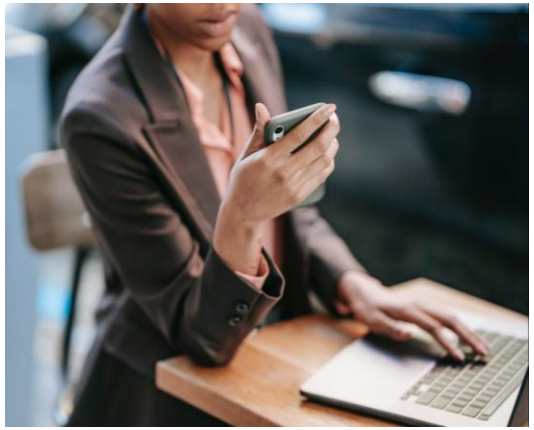
HITLab

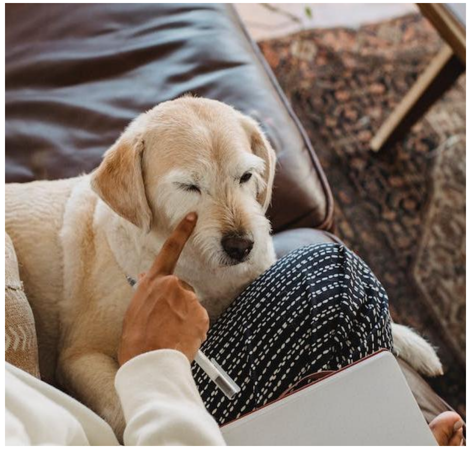
TU Delft

Touching and feeling surfaces: A crucial task for humans







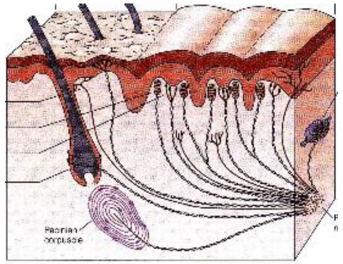



Tactile surface perception

skin-surface contact

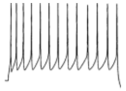
skin deformation

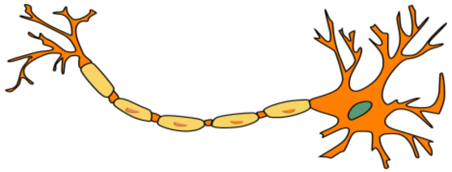
pressure
shear
vibration
thermal



stimulation of touch receptors

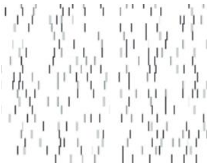
action potentials

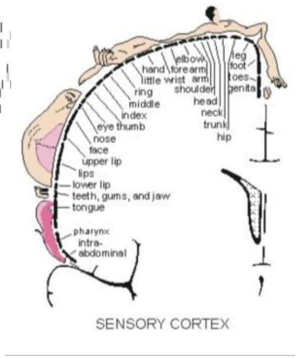


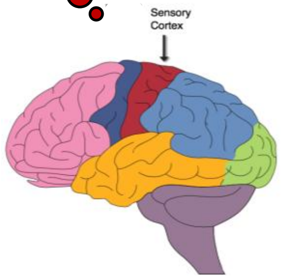


afferent neural signal transmission

neural codes





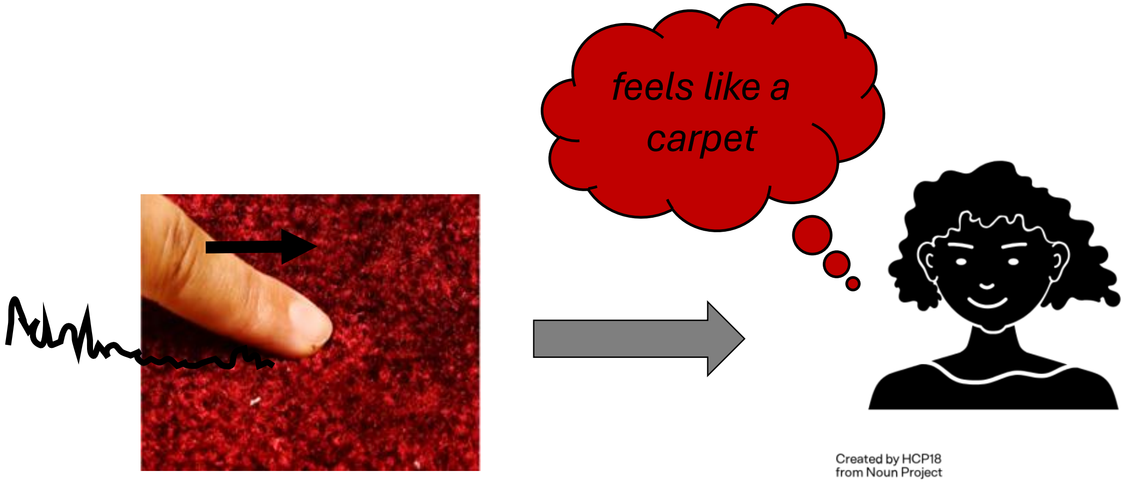


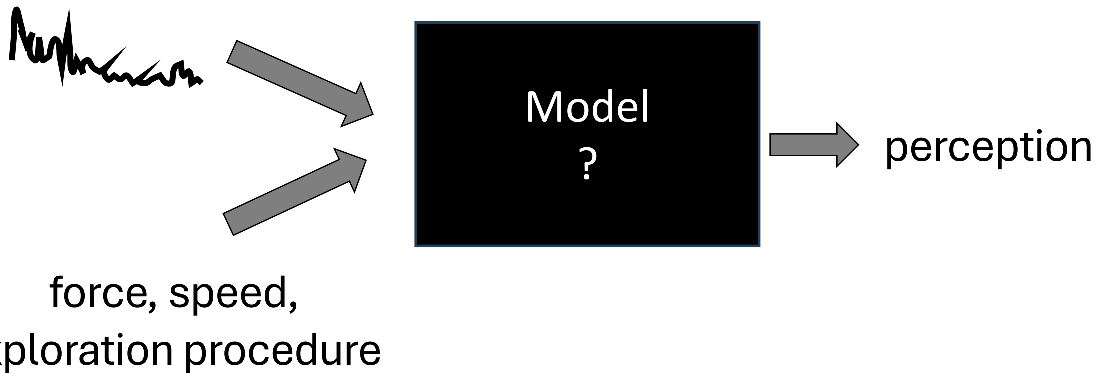
central nervous system

user exploration
(force, speed, exploration procedure)

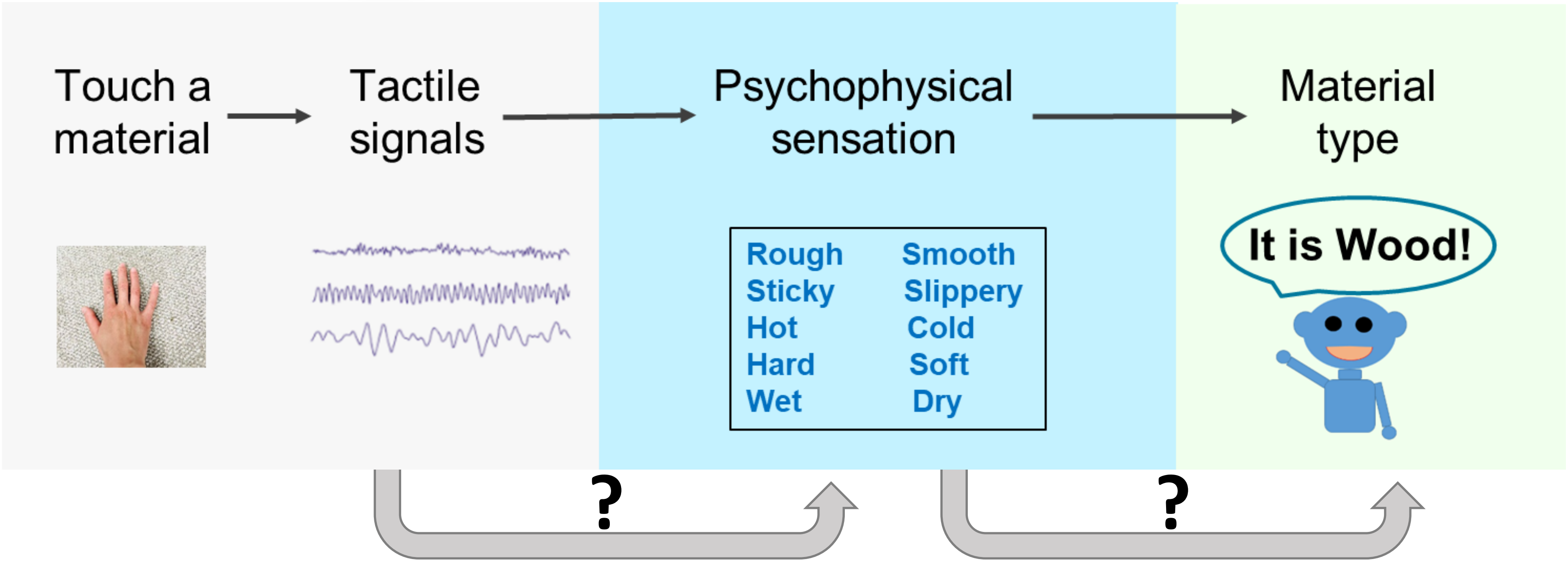
information from other senses

Can tactile data predict human perception?





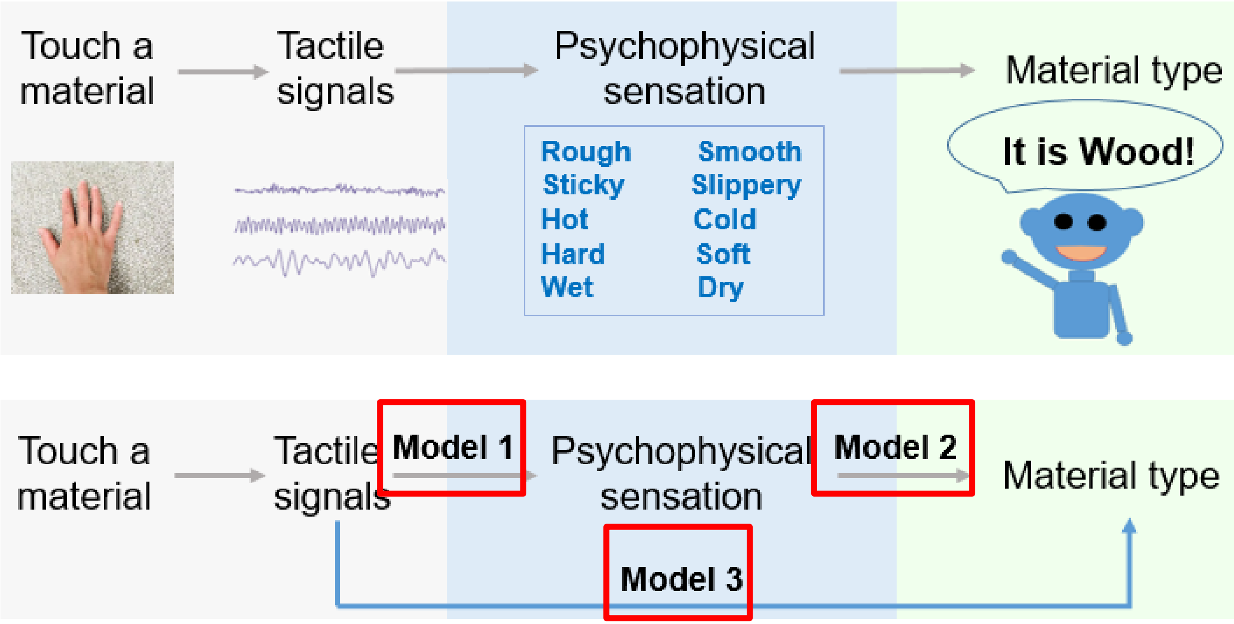
Material type



What our work is about?

Predicting materials and their perceptual attributes from tactile signals

Methods



Model 1: Capture the initial stage of human perception; (regression)

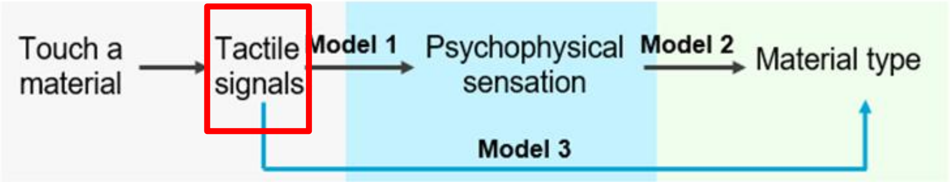
Model 2: Mirror higher-level perception processing; (classification)

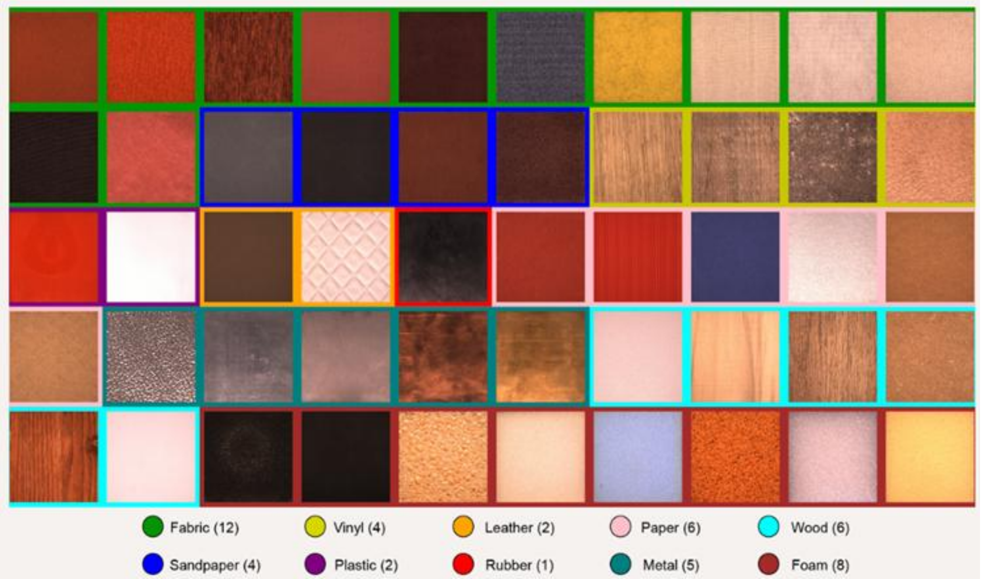
Model 1+ Model 2: Simulate the sequential nature of human haptic perception;

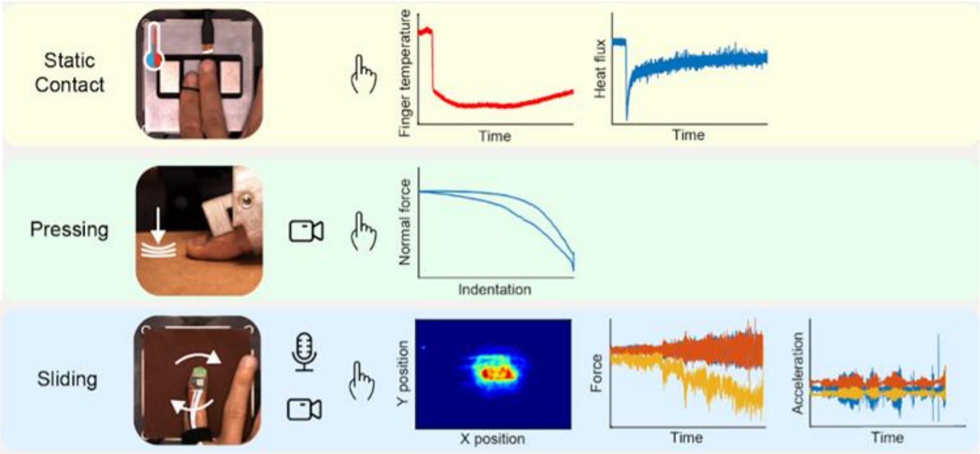
Model 3: Reveal the AI's inherent classification capabilities without human perceptual constraints. (classification)

Supervised machine learning:
Random Forest, Bagging Classifier, Logistic Regression, Support Vector machine...

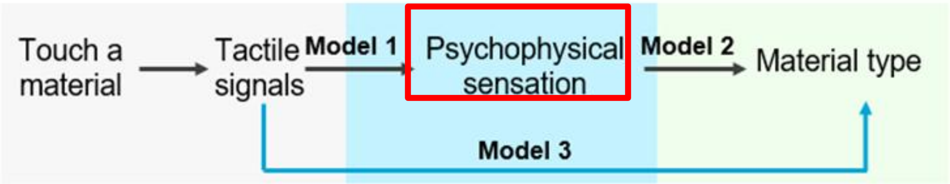
Data

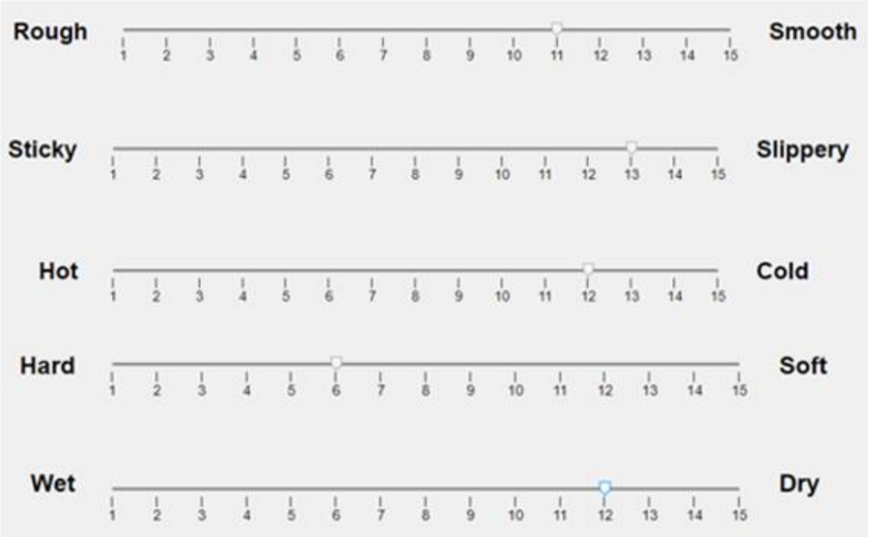






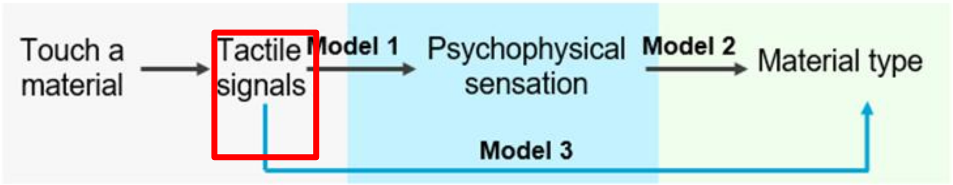
https://www.sens3.net/home

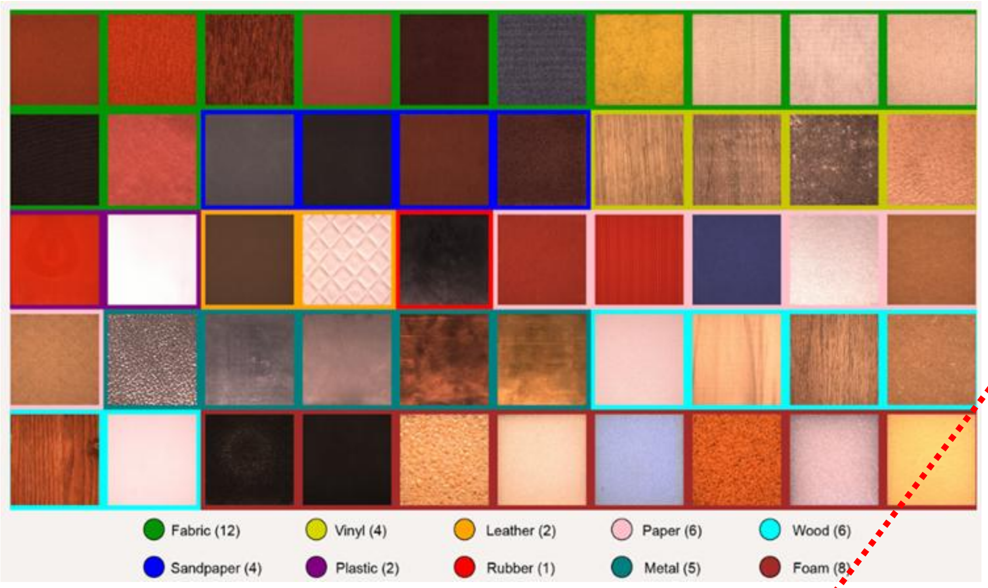


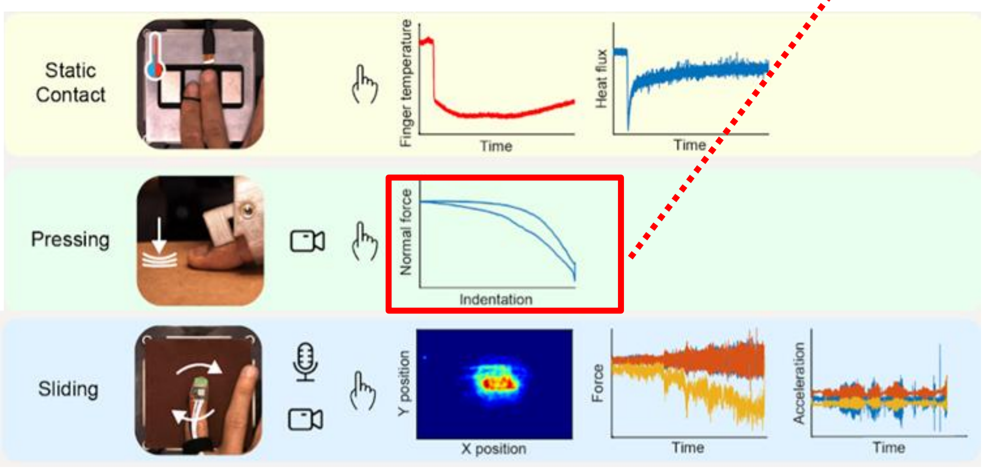


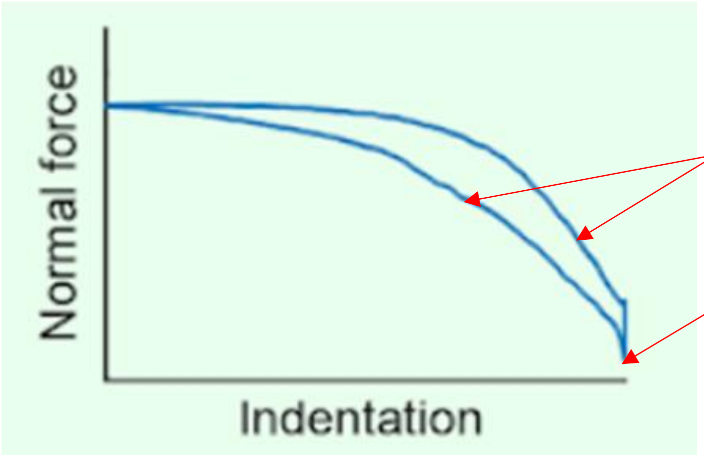
50 materials
20 participants

Feature extraction









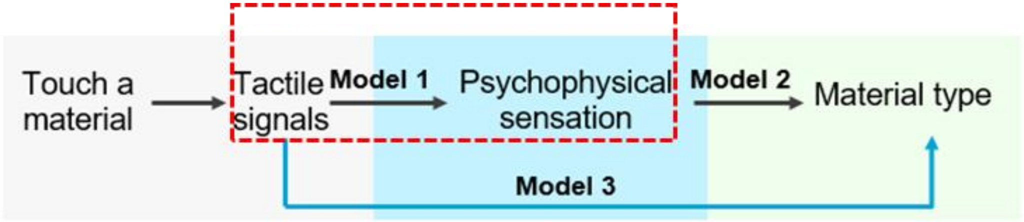
Rate of decay

Maximum indentation depth

			Physical features
P1			a*(1-exp(-x*b)) (stage 1)
P2			a*(1-exp(-x*b)) (stage 1)
P3	Pressing		identation difference
P4			a*(1-exp(-x*b))+c (stage 2)
P5			a*(1-exp(-x*b))+c (stage 2)
P6			a*(1-exp(-x*b))+c (stage 2)
T1			a/(1+exp(-b*(x-c))) (heatflux stage1)
T2			a/(1+exp(-b*(x-c))) (heatflux stage1)
T3			a/(1+exp(-b*(x-c))) (heatflux stage1)
T4		heatflux	a*x^b+c (heatflux stage 2)
T5	Thermal		a*x^b+c (heatflux stage 2)
T6			a*x^b+c (heatflux stage 2)
T7			initial temperature
T8		temperature	lowest temperature
T9			highest temperatrue after the lowest point
T10			temperature(end)-temperature(beigin)
S1			mean
S2			std
S3			rms
S4			max(abs)
S5			skewness
S6			kurtosis
S7			shape factor
S8			impulse factor
S9			crest factor
S10			clearance factor
S11		lateral	total harmonic distrotion
S12			sinad
S13			Friction Coefficient
S14			average power
S15			spectral centroid
S16			spectral spread
S17			spetral rolloff
S18			flatness
S19			bandwidth
S20			peak frequency
S21			energy band1
S22	Sliding		energy band2
S23			mean
S24			std

59 features

Results: tactile to sensation



Tactile to senstaion					
Mean squared error (MSE)					
Sensation	**Null model**	**Pressing**	**Thermal**	**Sliding**	**P+T+S**
Rough-Smooth	1.09	0.66	0.49	0.54	0.47
Sticky-Slippery	0.65	0.21	0.26	0.29	0.25
Hot-Cold	1.03	0.67	0.06	0.52	0.09
Hard-Soft	1.19	0.36	0.14	0.61	0.15
Wet-Dry	0.57	0.27	0.17	0.15	0.13

Rsquared					
Sensation	**Null model**	**Pressing**	**Thermal**	**Sliding**	**P+T+S**
Rough-Smooth	0	0.16	0.32	0.26	0.32
Sticky-Slippery	0	0.35	0.22	0.19	0.28
Hot-Cold	0	0.12	0.86	0.22	0.83
Hard-Soft	0	0.47	0.78	0.26	0.77
Wet-Dry	0	0.08	0.33	0.35	0.43

Spearman Correlation	Rough-Smooth	Sticky-Slippery	Hot-Cold	Hard-Soft	Wet-Dry
Rough-Smooth	1.00	0.63	0.66	-0.67	-0.56
Sticky-Slippery	0.63	1.00	0.49	-0.55	-0.32
Hot-Cold	0.66	0.49	1.00	-0.92	-0.81
Hard-Soft	-0.67	-0.55	-0.92	1.00	0.65
Wet-Dry	-0.56	-0.32	-0.81	0.65	1.00

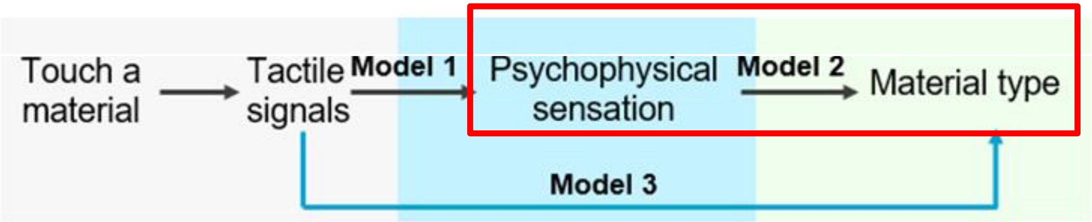
Metal
Hard and cold

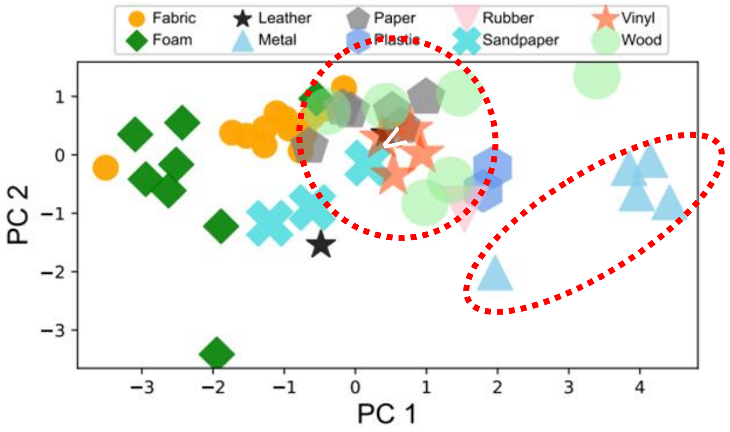
Fabric
Soft and warm

1.Our data and model perform better than null model;

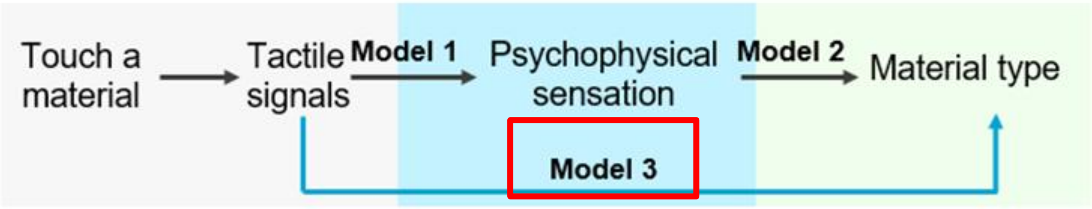
2.Thermal data can predict hot-cold, hard-soft very well.

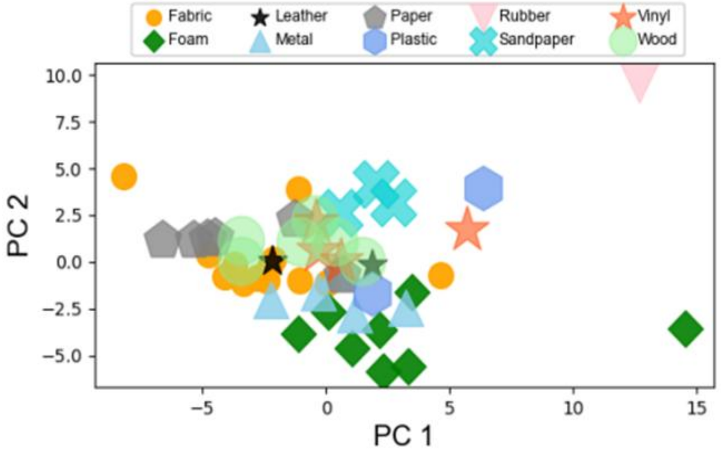
Results: sensation to material and tactile to material





Sensation to material	
Models	**Accuracy**
GaussianNB	0.77
MLPClassifier	0.74
RandomForest	0.73
LogisticRegression	0.71
KNN	0.69
SVM	0.69
BaggingClassifier	0.69
NearestCentroid	0.68
GradientBoosting	0.68
BernoulliNB	0.47
Null model 2	0.18
Null model 1	0.14



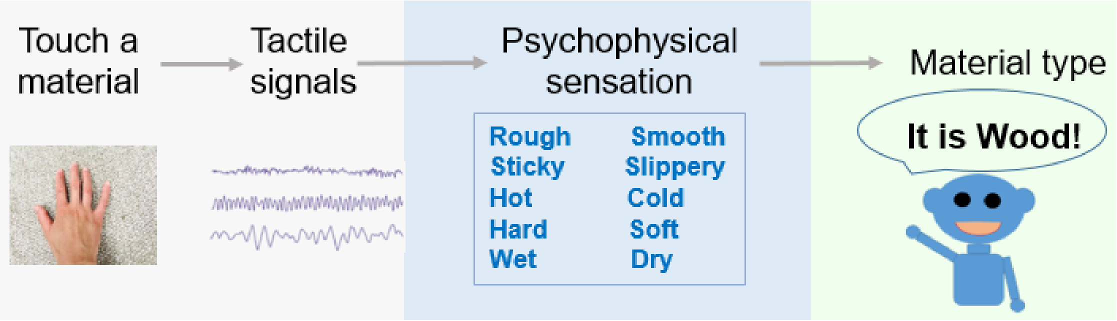


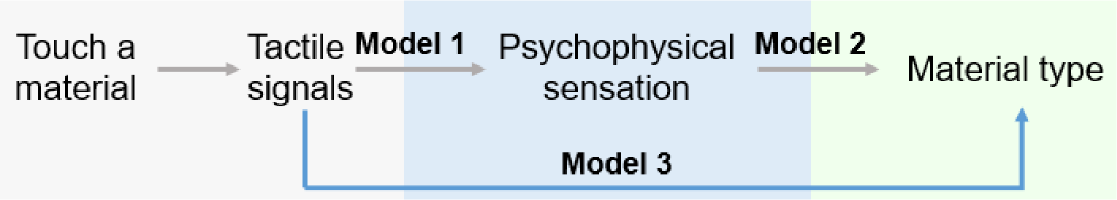
Tactile to material				
Models	**Pressing**	**Thermal**	**Sliding**	**All**
BaggingClassifier	0.39	0.90	0.40	0.86
RandomForest	0.41	0.90	0.46	0.85
SVM	0.38	0.79	0.35	0.69
BernoulliNB	0.43	0.67	0.41	0.67
LogisticRegression	0.38	0.76	0.38	0.66
NearestCentroid	0.36	0.80	0.42	0.66
KNN	0.42	0.75	0.35	0.65
MLPClassifier	0.45	0.81	0.39	0.65
GaussianNB	0.34	0.83	0.29	0.64
GradientBoosting	0.37	0.69	0.33	0.63
Null model 2	0.18			
Null`model 1	0.14			

Conclusion

What our work is about?

Predicting materials and their perceptual attributes from tactile signals





Key contribution of this work:
1. Extracted 59 features;
2. Build a framework to decode tactile signal information;
3. Employed ML models to perform various prediction tasks.
4. Identified the specific contribution of each sensation rating and each data type to the overall prediction performance.

Thank you, questions?