Introduction to Recognition

Saurabh Gupta

Many slides from Justin Johnson

Computer Vision

To extract "meaning" from pixels



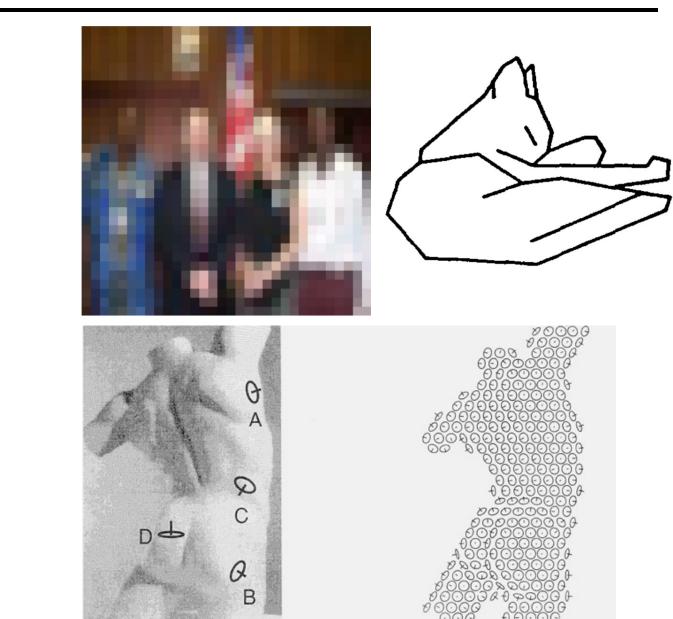
Meaning can take different forms:

- Geometric Inferences
- Semantic Inferences
- Inferences about actions

person, motorcycle, car, chair

Computer vision is easy for humans

- Effortlessly analyze images for a variety of tasks
- Infer semantics even from severely ablated
- Can also make precise inference about certain geometric properties



Yet has proven very hard for computers

 Computer vision research easily goes back 60 years ...

> MASSACHUSETTS INSTITUTE OF TECHNOLOGY PROJECT MAC

Artificial Intelligence Group Vision Memo. No. 100. July 7, 1966

HE SUMMER VISION PROJECT

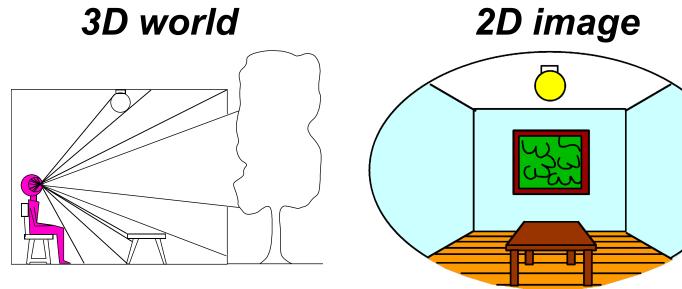
Seymour Papert

The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".



 Entirely true as of 2014 (or so) when this <u>xkcd</u> was published

• Images are a lossy projection of the world





Point of observation

Geometry information is lost

• Images are a lossy projection of the world

What color is the dress?

- A) Black and blue
- B) White and gold?

Appearance information is also lost



https://www.wired.com/2015/02/science-one-agrees-color-dress/

• Images are a lossy projection of the world



Might cause objects to blend

- Images are a lossy projection of the world (geometry, appearance, ... are lost)
- Visual world is diverse



Shape variation

- Images are a lossy projection of the world (geometry, appearance, ... are lost)
- Visual world is diverse



Background clutter



Occlusion

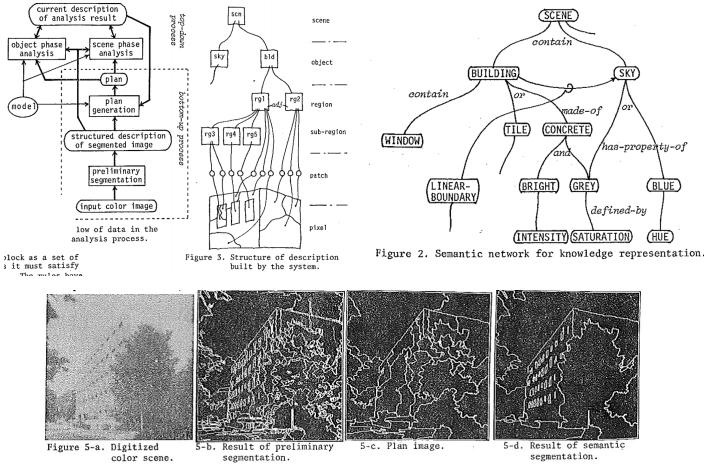
- Images are a lossy projection of the world (geometry, appearance, ... are lost)
 - need some priors to interpret what you are seeing
- Visual world is diverse
 - can't write down these priors by hand



John's Diner with John's Chevelle, 2007

Enter machine learning

 Good old-fashioned AI (GOFAI) answer: Program expertise into the agent



Y. Ohta, T. Kanade and T. Sakai. <u>An Analysis System for Scenes Containing objects with Substructures</u>. Proc. of the Fourth International Joint Conference on Pattern Recognition, pp. 752-754, 1978

 Good old-fashioned AI (GOFAI) answer: Program expertise into the agent

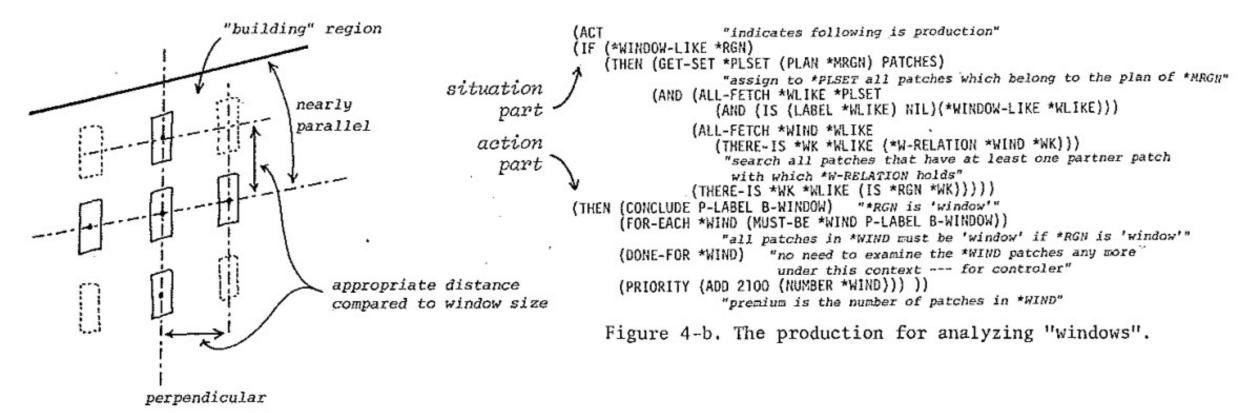


Figure 4-a. "Building" region and "windows".

 Good old-fashioned AI (GOFAI) answer: Program expertise into the agent

Appendix-B Complete Listing of the Model

eSCENE knowledge-black-of-scene

(OBJECTS (aSKY oTREE aBUILDING aRDAD aLNKNDUN) SUB-OBJECTS (aB-HINDON aCAR aC-SHADON) KEY-PATCH-IS (GREATERP (AREA aPCH) 328)(aPCH)]

PLAN-IMAGE-GENERATION ((DIV (BOUNDARY-LENGTH &PCH &KPCH) (MULT (R-G-B-DIFFERENCE &PCH &KPCH) (BOUNDARY-CONTRAST &PCH &KPCH)))

IF-PLAN-IS-MODIFIED (IF-DONE (

nula-ter-haizan-detettian (uc.t. (FFI (S) GHR (2014) (SEDE)) NLL) (uc.t. (FFI (S) GHR (2014) (SEDE)) NLL) (uc.t. (FFI (S) HR (2014) (SEDE)) (uc.t. (FEI (S) HR (2014) (SEDE)) (uc.t. (FEI (S) HR (2014) (SEDE)) (uc.t. (SEDE (S) HR (2014) (SEDE)) (UC.T. (SEDE) (SEDE) (SEDE)) (UC.T. (SEDE) (SEDE) (SEDE)) (UC.T. (SEDE) (SEDE) (SEDE)) (UC.T. (SEDE)) (SEDE) (SEDE)) (UC.T. (SEDE)) (SEDE) (SEDE)) (UC.T. (SEDE)) (SEDE)) (SEDE)) (UC.T. (SEDE)) (SEDE)) (SEDE)) (SEDE)) (UC.T. (SEDE)) (SED)) (SEDE)) (SED)) (SED)) (SED)) (SED)) (SED)) (SE

P-SELECT (10-00 (

rule_for—initial—start ((ACT (AND (PROBABLY BUILDING ⊘PCH)(NOTFOUND BUILDING))

rule+dr-rule=coclusion (LGC (M0 G40Mx exP0 (uxPer8 ePc)) (THECT (M0 G40Mx ePc) (uPc)(LGC (M0 G4Pc 510E)) (THECT 51 art #ESIGN (M0 G1 5 u.Ret, HTT) TEE) (M0 G1 5 u.Ret, HTT) TEE) (M0 G1 6 u.Ret, HTT) TEE) (M0 G1 6 u.Ret, HTT) (M0 G1 0 u.Ret, HTT) (M0 G1 0

rule-for-tree-garbage ((ACT (PR0GABLY TREE #CCH) (THEN (CONCLUGE P-LABEL TREE) (SCORE-IS (ASK-VALUE TREE #PCH)))(#PCH)]))

P-LABEL (IF-DONE (

if-done-rule-to-be-activated-when-Keypatch-is-labeled [(ACT (NOT (IS (OF PLAN APCH) NIL)) (THEN (EXECUTE PLAN-EVALUATION))) (sPCH)])))

⇔SKY knowledge-block-of-sky

(PROPERTY-RULES ((IGN (NOT (.4.DWER #RDN))(1.8, 8.6))(#RDN)) (IGN (NOT (.8.DWER #RDN))(1.8, 8.2))(#RDN) (IGN (NOT (.4.DWER #RDN))(1.8, 8.2))(#RDN) (IGN (NOT (.4.DWER #RDN))(1.8, 8.7))(#RDN) (IGR (NOTMENDE #RDN U-5.0(8.7, 8.2))(#RDN))

 RELATION-RALES (
 (1618: 400.01.405.44: 60.00.447.14: 60.01.401.41: 60.01.41:

(HER LORACLE F-LABL NUMBIN) (SOR-15 LOB - AL CONFIDENCE-VALLE #POIII))(#POII) (IACT LOB (PROBLEY, ROU #POI INDIVIDUE FORD) (HER LORACLEY F-LABL ROU (CODE-15 LOB + AL CONFIDENCE-VALLE #POIII)))(#POII) (CODE-15 LOB + AL EXCONFIDENCE-VALLE #POIII)))(#POII) (CODE-15 LOB + AL EXCONFIDENCE-VALLE #POIII)))(#POII) (CODE-15 LOB + AL EXCONFIDENCE-VALLE #POIII)))))))) (HER LORACLE F-LABL RED (CODE-15 LOB + AL EXCONFIDENCE-VALLE #POII))))))))))))))))

relie for --adjecent-ual i-d-foulieling fuer: UAD UN-4-RETURNE #VERTURNE (ADD US-RETURNE #VERTURNE UAD US-LURLE, #4. BUILDING UAD US-LURLE, #4. BUILDING USFERDE-DEE #VERTURNE USFERDE-DEE #VERTURNE (SUBCE 1-400-E UNI MALCOT #U)) (SUBCE 1-600-E UNI MALCOT #U)) (SUBCE 1-600-E UNI MALCOT #U))

Pula-to-au) (Hey-sectular (IACT AUD DVX - BULLIDE AFON (ADD C) (ADD C

P-SELECT (

T0-DDI (UACT 104X-BE SKY #PCH) (THEN (SCORE-15 ALDI 2.0 (ASK-VALUE SKY #PCH))))(#PCH)) (KACT (ANO (S-H-NA) #PCH #PKRN(GRI(GRI #PCH)) (THEN (SCORE-15 2.0))(#PCH #PRRN1) (KACT (GRIGAT #PCH) THEN (SCORE-15 0.05))(#PCH))

IF-DONE ([(ACT oTo (THEN (CONCLUDE P-LABEL SKY) . (CONCLUDE R-MERGE (MASTER oPCH))))(oPCH)]))

APRIORI-VALUE-IS 0.1)

sTREE knowledge-block-of-tree

(MADE-OF (WLEAVES)

PROPERTY-RULES ([(GEN (wMIDDLE #RGN)(8.5 . 8.3))(wRGN)] [(STR (wHEAVY-TEXTURE #RGN)(8.8 . 8.2))(wRGN)])

P-SELECT (

 IO-LOU (
 (HAP-BE TREE #PCH)

 (IACT (HAP-BE TREE #PCH)
 (ADC 2.8 (ASK-VALLE TREE #PCH)))) (#PCH)

 (IACT (AND (IS-PLAN #PCH #RCN) 0007 (#SHINING #PCH)))
 (HOPCH)))

 (THEN (BCORE-IS 3.8))) (#PCH #RCN)
 (HOPCH))

IF-UUNE ([(ACT *T* (THEN (CONCLUDE P-LABEL TREE) (CONCLUDE R-MERGE (MASTER *PCH))))(*PCH)]))

APRIORI-VALUE-IS 8.2)

sBUILDING knowledge-block-of-building

(MADE-OF (OR ±CONCRETE ±TILE ±BRICK) SUB-OBJECTS (±B-WINDOW)

PROPERTY-RULES ([IOEN (#11DDLE #RGN) (8.6 . 8.3)) (#RGN)] [ISTR (#1AN/HOLE #RGN) (8.8 . 8.2)) (#RGN)] [ISTR (#1AN/LINE #RGN) (8.4 . 8.2)) (#RGN)] [IOEN (#HOLE).INE #RGN) (8.5 . 8.2)) (#RGN)]

BELATION-BULES (

RELATION-RULES ((IGEN UANG (WLINEAR-BOLINDARY WREN WREN) (IF WLINEAR-BOLINDARY (NOT (POSITION UP WREN WRENZ)))) (IF WLINEAR-BOLINDARY (NOT (POSITION UP WRENZ)) (ISTR (IF (NOT (IS (OF BUILDING-ZONE (SCENE)) NIL)) (AND (0-RATIO #REN (OF BUILDING-ZONE (SCENE))) (aMANYLINE aRGN))) (0.9 . 0.3) FOR SCENE)(aRGN)] P-SELECT (((ACT (AND (MAY-BE BUILDING «PCH) (SAME-ZONE «PCH «MRGN)) (THEN (CONCLUDE P-LABEL BUILDING) (CONCLUDE R-MERGE #MRGN) (SCORE-IS (ADD 2.0 (ASK-VALUE BUILDING sPCH)))) (oPCH oMRGN) L(ACT (AND (NOT (IS-PLAN «PCH «MEDN)) (SAME-ZONE «PCH «MEDN)) (MAY-BE BUILDING (PLAN #PCH))) (THEN (CONCLUDE P-LABEL BUILDING) (CONCLUDE R-MERGE #MRGN) (SCORE-IS (ADD 1.95 (ASK-VALUE BUILDING (PLAN #PCH))))) («PCH «MRGN) rule-for-window-extraction LIACT (IF (AND (IS-PUN) APCH WRON) (SAME-ZONE «PCH WRON) (AVERTICALLY-LONG «PCH (ISONTACT «PCH (PLAN WRON))) (THEN (GET-SET «PLSET (PLAN WRON) PATCHES) (AND (ALL-FETCH WALIKE WPLSE (AND (IS (LABEL WULLKE) NIL) (SAME_ZONE ALL IKE AMBON (AVERTICALLY JUNG AND 18 (#CONTACT #WLIKE (PLAN #MRGN))))

> (1995-19 447 44.175 (447-64.170) 4701 4401) (41.4-1570 4480 44.175 (1995-19 447 44.176 (1995-19 447 44.176 44.176) (1995-19 447 44.176 44.176) (1995-19 4400 2-1 017 467-45 44.170 P-LARE 8-411004) (002-279 44.1701) (500F-19 4400 2-1 017 4407-57 44.170 (24.176)) (500F-19 4400 2-1 017 4407-57 44.170 (24.176)) (500F-19 4400 2-1 017 4407-57 44.170) (100-115-2.14 470 470-1017) (100-115-2.14 470 470-1017) (100-115-2.14 470 470-1017) (100-115-2.14 470 470-1017)

D-MERGE (IF-DONE ([(ACT wTw (DESCRIBE-BUILDING (REGION wPCH)))(wPCH))))

O-CREATE (1F-DONE ([(ACT wTw (THEN (EXTRACT-BUILDING-SHAPE (REGION #PCH)) (DESCRIBE-BUILDING (REGION #PCH)) (EXECUTE PLAN-EVALUATION))(#PCH)]))

APRIORI-VALUE-IS 8.2)

wROAD knowledge-block-of-road

(MADE-OF (OR #ASPHALT #CONCRETE) SUB-OBJECTS (#CAR #C-SHADDW)

> PROPERTY-RULES ((IGEN (4_DUBER #FR0)(8.8.8.4))(#RGN)) (IGEN (4+D0R120NTALLY-LONG #RGN)(8.7.8.2))(#RGN)) (ISTR (TOUCHING #RGN LOWER-SIDE)(8.9.8.2))(#RGN)))

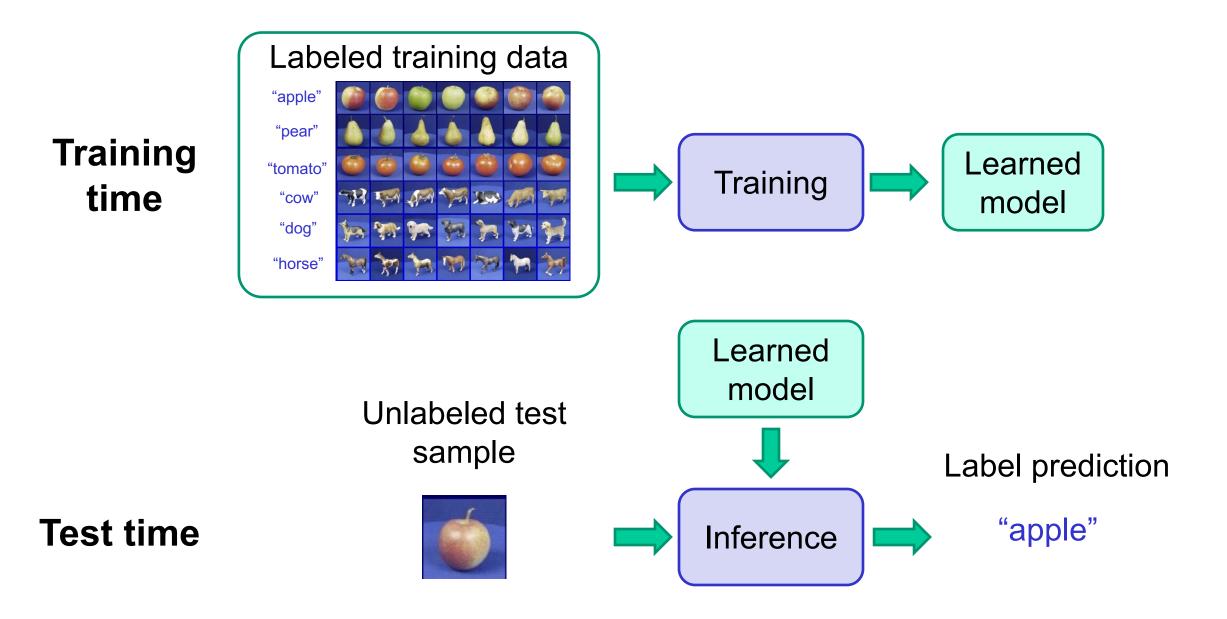
 RELATION-RELES
 I

 (ISTR IAMO (addres-COLOR ARDI) ARRAY (TOUCHING ARDI ARDA) ((0, -9, -8, -2) FOR ROAD) (addres ARDA2) ((0, -0, -1) (15) (30 FORT(20 CSCH2) TOUC) ((0, -0, -1) (15) (30 FORT(20 CSCH2) TOUC) ((0, -0, -1) (15) (30 FORT(20 CSCH2) ((0, -0, -2) FOR SOCHE) (ARDA1) ((1, 0, -0, -2) FOR SOCHE) (ARDA1)

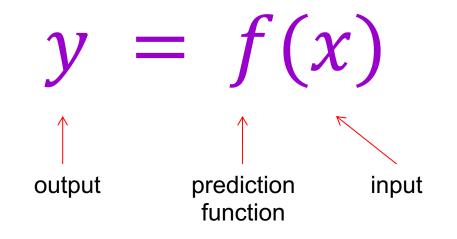
- Good old-fashioned AI (GOFAI) answer: Program expertise into the agent
 - Never worked (in general)

- Good old-fashioned AI (GOFAI) answer: Program expertise into the agent
- Modern answer: Program into the agent the ability to improve performance based on experience
 - Experience should come from *training data* or *demonstrations*
 - We want to optimize the performance of the agent on the training data, with the hope that it will *generalize* to unseen inputs
 - This is the *statistical learning* viewpoint

The basic ML framework (for supervised learning)



The basic ML framework (for supervised learning)





- Training (or learning): given a training set of labeled examples {(x₁, y₁), ..., (x_N, y_N)}, instantiate a predictor f
- **Testing** (or **inference**): apply f to a new *test example x* and output the predicted value y = f(x)
- Rather than hand-defining how 2D projections of apples are different from pears, f will learn this from the data.



Deep Learning

• A general way to model function *f* as composition (layers) of simple functions, very loosely inspired by the brain.

Lecture overview

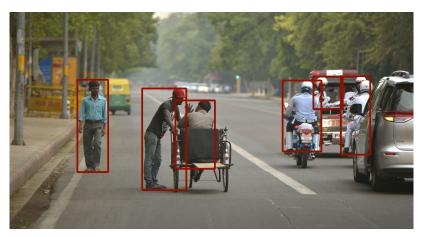
- Different recognition problems in computer vision
- Supervised classification
- Taxonomy of learning problems

Different Recognition Problems

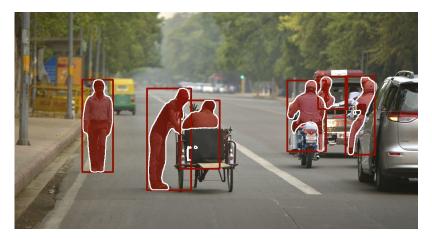


<u>This image</u> by <u>Nikita</u> is licensed under <u>CC-BY 2.0</u>

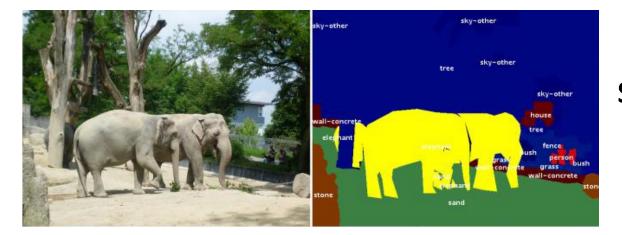
Classification: Assign image to one of a fixed set of categories



Object Detection: Put a bounding box around each instance of a class



Instance Segmentation: Mark pixels for each instance of a class



Semantic Segmentation: Label each pixels with its category

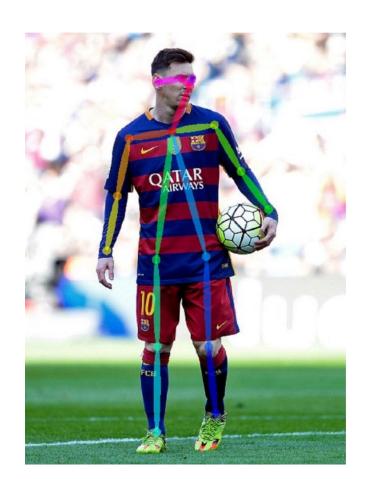
Different Recognition Problems



Image Captioning: Man riding a horse on a beach

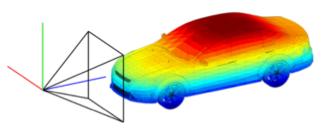


Depth Prediction: how far is each pixel in the image



Keypoint prediction



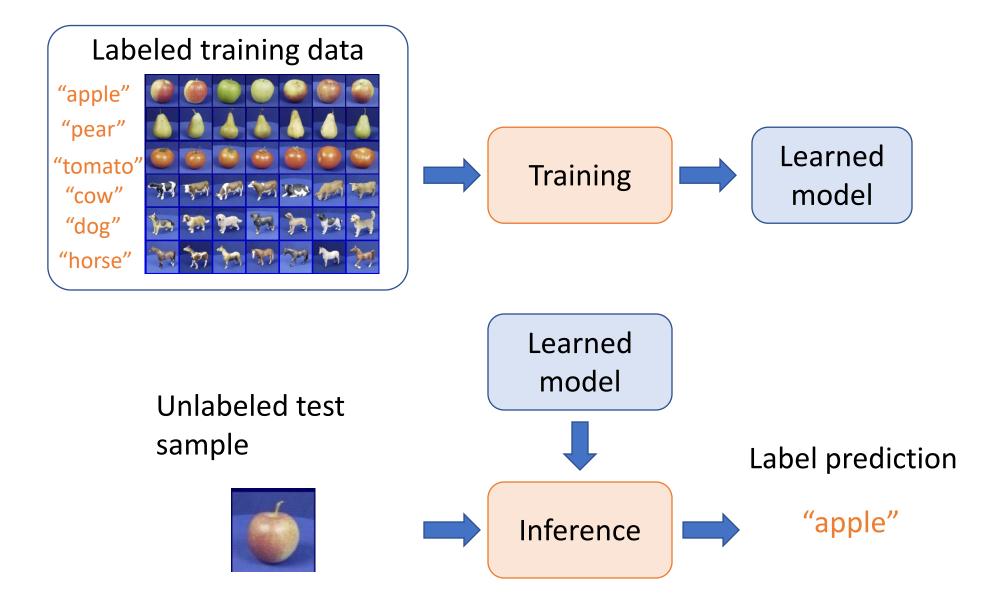


Pose Prediction: Rotation that aligns object to a canonical pose

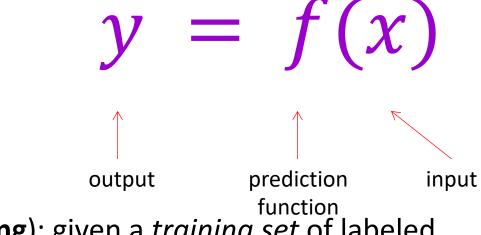
The basic ML framework (for supervised learning)

Training time

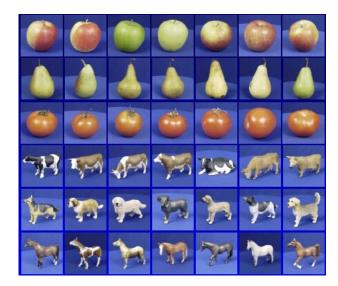
Test time



The basic ML framework (for supervised learning)



- **Training** (or **learning**): given a *training set* of labeled examples $\{(x_1, y_1), \dots, (x_N, y_N)\}$, instantiate a predictor f
- **Testing** (or **inference**): apply f to a new *test example x* and output the predicted value y = f(x)





 Rather than hand-defining how 2D projections of apples are different from pears, f will learn this from the data.

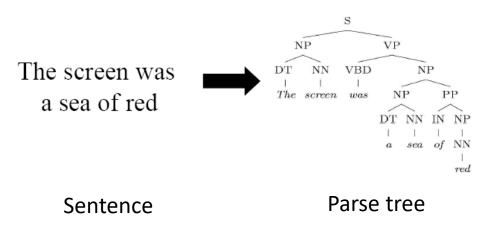
Is an image classifier all you need?

- Image Classification
- Object Detection
- Instance Segmentation
- Semantic Segmentation
- Image Captioning
- Depth Prediction
- Keypoint Prediction
- Pose Prediction



Taxonomy of learning problems

- Type of output
 - Classification
 - Regression
 - y = f(x). y is an arbitrary scalar and not a class label.
 - Structured prediction
 - y = f(x). y is a structured object.





Depth Prediction: how far is each pixel in the image

Several computer vision problems have structure in the output space, but often solving a classification problem with some simple post-processing (or even without) ends up being sufficient.