Image Anlysis: lessons, challenges, and meta questions

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April 7, 2025

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- Grain of sand on a (growing) beach

How it all started

HOW IT ALL STARTED

How it all started

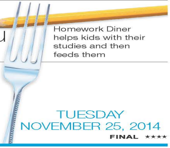
NEAR UPSET

UNM women give No. 5 Stanford a scare in the Pit

SPORTS >> D1

Schoolwork on the menu

EDUCATION >> B4



Homework Diner helps kids with their studies and then feeds them

NEW MEXICO'S LEADING NEWS SOURCE

ALBUQUERQUE JOURNAL

ABQJOURNAL.COM

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TUESDAY NOVEMBER 25, 2014

FINAL ★★★★

ESTABLISHED 1880

Father: 'I cannot forgive the man who killed my child'

UNM students Joseph Mendoza, left, and Briana Hillard. Hillard was killed and Mendoza hurt in a car crash Friday night.

GRANT: Died after car he was riding in was struck

THOMPSON: Injured but released from hospital

Man describes son's final breaths after deadly crash

BY NICOLE PEREZ
JOURNAL STAFF WRITER

Myron Grant sat in a University of New Mexico Hospital room Saturday night, holding his son's hand. Matthew Grant was on life support, mouth filled with gauze, his chest moving involuntarily as he opened his mouth every few minutes.

"I was watching how far it was between each breath. They got farther and farther and farther apart. He took one more breath and there was not another one in 5 minutes, in 10 minutes, in 30 minutes, in an hour," Myron Grant said.

Matthew Grant, 21, took his last apparent breath at 7:27 p.m. Saturday and was officially pronounced dead hours later.

He died after a driver rammed into a car carrying him and three other University of New Mexico students near Rio Grande and Mountain late Friday night while the group was on its way to a house party.

The crash also killed 21-year-old Briana Hillard and seriously injured 21-year-old Joseph Mendoza and Julia Thompson, all UNM students. Mendoza was released from the hospital Sunday, and Thompson was expected to be released Monday night, accord-

See STUDENT'S >> A4

No Ferguson indictment

Prosecutor cites conflicting testimony; president calls for peaceful response as crowds demonstrate, set fires

BY JIM SALTER AND DAVID A. LIEB
THE ASSOCIATED PRESS

FERGUSON, Mo. — A grand jury declined Monday to indict white police officer Darren Wilson in the death of Michael Brown, the unarmed, black 18-year-old whose fatal shooting sparked weeks of sometimes-violent protests and inflamed deep racial tensions between many African-Americans and police.

Moments after the announcement by St. Louis County's top prosecutor, crowds began pouring into Ferguson streets to protest the decision. Some taunted police, broke windows and vandalized cars. Within a few hours, several buildings were ablaze, and frequent gunfire was heard. Officers used tear gas to try to disperse some of the gatherings.

Prosecuting Attorney Bob McCulloch said the jury of nine whites and three blacks met on 25 separate days, hearing more than 70 hours of testimony from about 60 witnesses, including three medical examiners and experts on blood, toxicology and firearms.

"They are the only people that have heard and examined every witness and every piece of evidence," he said, adding that the jurors "poured their hearts and soul into this process."

As McCulloch read his statement, Michael Brown's mother, Lesley McSpadden, was sitting atop a vehicle listening to a

See NO INDICTMENT >> A4

ROBERT COHEN/THE ST. LOUIS POST-DISPATCH/THE ASSOCIATED PRESS

Lesley McSpadden, mother of Michael Brown, is comforted outside the Ferguson Police Department as she hears the announcement that Ferguson police officer Darren Wilson will not be indicted

Mayor Berry defies Dems with 4 vetoes

Measures involve Han case, inspector general, union negotiator

BY DAN MCKAY
JOURNAL STAFF WRITER

Mayor Richard Berry clashed with City Council Democrats in a big way Monday, vetoing four bills that had passed along party lines this month.

Berry, a Republican, blocked proposals that sought to revive the inspector general's office at City Hall, limit when city attorneys can seek to recover legal fees in court and require council approval before hiring someone to negotiate with unions.

BERRY: None of his 16 vetoes has been overturned

A fourth proposal vetoed called on the city attorney to drop a request for legal fees in a lawsuit filed by the family of Mary Han, a prominent civil-rights attorney who died in 2010.

Altogether, it was the largest batch of bills ever vetoed by the mayor in one day.

"These bills were contradictory to existing law, or they set bad precedent for the city moving forward," Berry said in an interview.

Each of the bills narrowly had won approval, on 5-4 votes, with Democrats in the majority.

Berry's vetoes will stand unless a Republican councilor changes positions. It takes six of nine councilors to override a veto.

City Council President Ken Sanchez, a Democrat, said he wasn't sure whether councilors even would attempt an override.

"I'm very disappointed," he said, "but I kind of anticipated that was going to happen. This year, more than ever before, we've seen more veto messages come down to the council."

See MAYOR >> A2

TIM GROBATY
Don't be a turkey! Call a tip line for kitchen help
Local » A3

GOVERNMENT
Defense Secretary Chuck Hagel steps down
Nation » A10

MLB
Ex-Dodger Ramirez signs with Red Sox
Sports

PRESS-TELEGRAM
Serving the Greater Long Beach area since 1897
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LONG BEACH
SUNNY AND VERY WARM
High: 82 Low: 50 » PAGE A16

Tuesday, November 25, 2014 $1.00 FACEBOOK.COM/PRESSTELEGRAM TWITTER.COM/PRESSTELEGRAM **presstelegram.com**

RACIAL TENSION

NO INDICTMENT IN FERGUSON CASE

Grand jury: Decision in killing of black teen by white cop sends crowds pouring into streets

THANKSGIVING

Heavy holiday traffic is expected

Auto Club forecasts travel for period will be highest in 7 years

By Gregory J. Wilcox
greg.wilcox@langnews.com
@dngregwilcox on Twitter

Holiday revelers are expected to hit Southern California roads and take to the skies in the largest number in seven years over the Thanksgiving weekend, thanks to dramatically lower gasoline prices and improving personal finances, officials said Monday.

The Automobile Club of Southern California is predicting 3.5 million local residents will take a trip of 50 miles or more over the long weekend, an increase of 3.8 percent from last year. That's the most since 4 million in 2007.

Statewide 5.65 million are expected to take a Thanksgiving trip, also up 3.8 percent from a year ago and the most since 6.44 million in 2007.

"As Californians see improvements in jobs and household worth this year, they are more willing to spend on travel," Auto Club spokesman Jeffrey Spring said. "An added bonus for travel budgets has been dramatically lower gas prices in the past two months. Consumers have more money in their pockets to plan trips, and this Thanksgiving's

FOSTER ANIMALS
TEMPORARY HOMES FOR PETS
LOCAL 1C

TURKEY RUN
THOUSANDS OF CARS COMING TO SPEEDWAY THIS WEEK
LIFE ETC. 1D

ARCHRIVALS
FSU & UF READY FOR SHOWDOWN
SPORTS 1B

THE DAYTONA BEACH
NEWS-JOURNAL
NEWS-JOURNALONLINE.COM
HOME OF THE WORLD'S MOST FAMOUS BEACH
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NOVEMBER 25, 2014
VOLUSIA EDITION 75 CENTS

FERGUSON, MISSOURI

NO CHARGES

Protests turn violent after officer not indicted for killing teen

Associated Press photos

A group of protesters vandalize a police vehicle Monday night after the announcement of the grand jury decision not to indict Police Officer Darren Wilson in the fatal shooting of Michael Brown, an unarmed black 18-year-old.

By JIM SALTER and DAVID A. LIEB
Associated Press

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heard. Officers released smoke and pepper spray to disperse the gatherings.

Prosecuting Attorney Bob McCulloch said the jury of nine whites and three blacks met on 25 sepa-

Defense secretary resigns

Hagel first Cabinet member to leave after election losses

By JULIE PACE and ROBERT BURNS
Associated Press

WASHINGTON — Defense Secretary Chuck Hagel announced Monday he is stepping down, leaving under pressure following a rocky tenure in which he has struggled to break through the White House's insular team of national security advisers.

During a White House ceremony, Obama said he and Hagel had determined it was an "appropriate time for him to complete his service."

CHUCK HAGEL

Hagel is the first senior Obama adviser to leave the administration following the sweeping losses for the president's party in the midterm elections. It also comes as the president's national security team has been battered by crises including the rise of Islamic State militants in Iraq and Syria and Russia's provocations in Ukraine.

The president praised Hagel, a Republican who grew close to Obama while they both served in the Senate,

SEE **RESIGNS,** PAGE 10A

YOUR HEALTH: Local physician leads U.S. in testing for breast cancer 'sub-type,' **D1**

The Post and Courier

THE SOUTH'S OLDEST DAILY NEWSPAPER • FOUNDED 1803

Tuesday, November 25, 2014 POSTANDCOURIER.COM Charleston, S.C. $1.00

Grand jury's decision sparks anger, violence

DAVID GOLDMAN/AP

Police in riot gear move down the street past a burning police car Monday night in Ferguson, Mo., after a grand jury decided not to indict Ferguson police officer Darren Wilson in the shooting death of 18-year-old Michael Brown.

Magnet parents file suit

Say characterization of watermelon ritual hurt sons' reputations

BY AMANDA KERR
akerr@postandcourier.com

The parents of three Academic Magnet High School football players have filed a defamation lawsuit claiming characterizations of the team's controversial postgame watermelon ritual damaged their sons' reputations.

Betty and James R. Moore Jr., Amy and Lee Garrard, and Dean and Kathryn Frailey are suing the Charleston County School District, consultant Kevin Clayton and his firm Axxis Consulting Co., and Jones Street Publishers LLC, which is the parent company of the Charleston City Paper, on behalf of their children, who are only named in the lawsuit by their initials.

Please see **LAWSUIT,** Page A6

USC women make history as No. 1, keep eyes on prize

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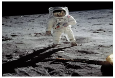
- Robert Cohen: role of media and photo journalists, and their impact on what we see and what we *never* see
- Too many images! No money :(→ Need for systematic, quick, and efficient analysis tools

Not the first one to notice that images might be important



10 Photos That Changed the Course of History

50 Famous Photos That Changed Our World

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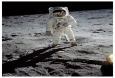



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 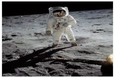    

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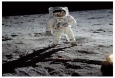



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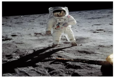



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 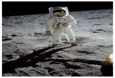    

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- Visual framing of movements: capturing reality + editorial footprints (Veneti 2017; DeLuca, Lawson, and Sun 2018; Torres 2023)

Overview of this talk

OVERVIEW OF THIS TALK

Overview of this talk (cont.)

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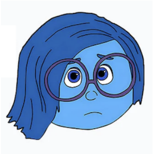

Puzzles

OVERVIEW OF THIS TALK (CONT.)

Puzzles

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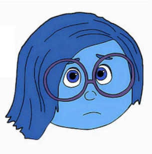

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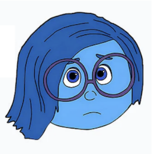

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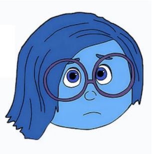

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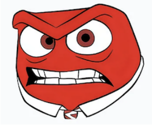

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Future

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  - ML tools as “black boxes” and disconnected from social sciences

Tools for Image Analysis: CNNs for Social Scientists

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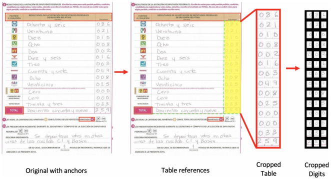

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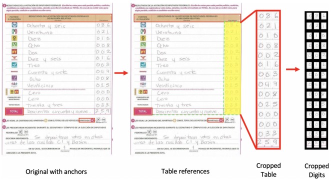

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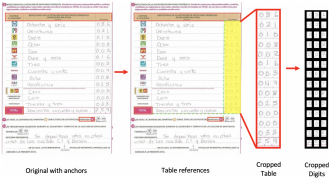
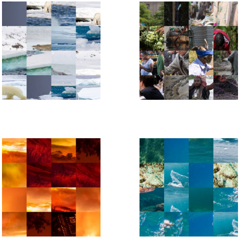
- Decrease the entry costs to the computer vision world: explanation, glossary, social science application, etc.



Tools for Image Analysis: The BoVW

- Development of the BoVW as a framework to "tokenize" images



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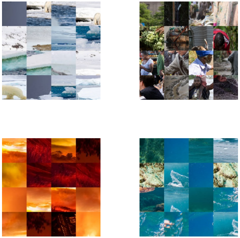

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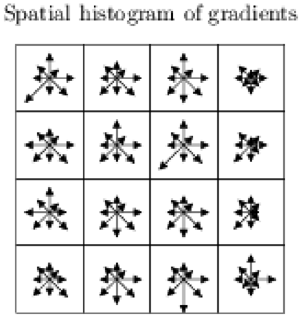
  2. Describe them with HoGs (changes in pixel intensity)



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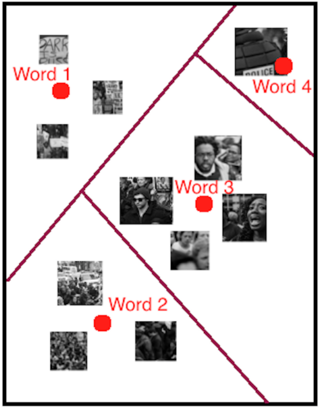

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Image			...	
	0	1	...	0
	0	1	...	1
	5	8	...	4

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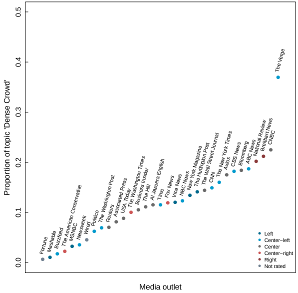
- Identify topics as visual frames



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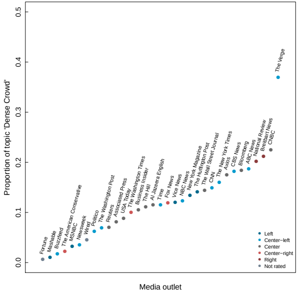

Tools for Image Analysis: The BoVW

- Development of the BoVW as a framework to "tokenize" images
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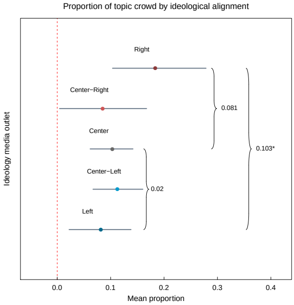

Tools for Image Analysis: Discovering Latent Treatments

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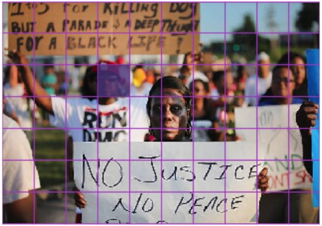

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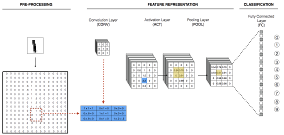

Figure 1. Example of a convolutional neural network structure.

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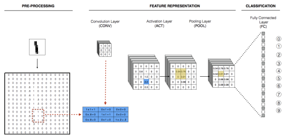

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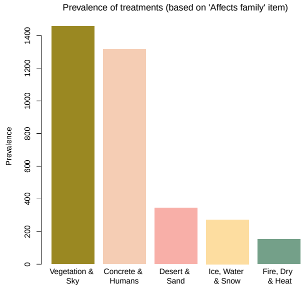

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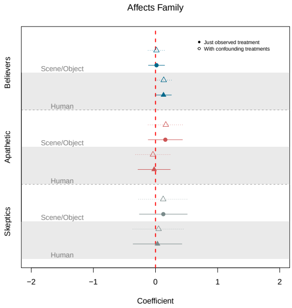
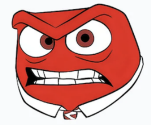


OBSTACLES AND SPEED BUMPS

- Dealing with difficult data

Obstacles and speed bumps



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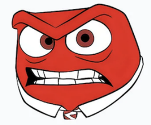

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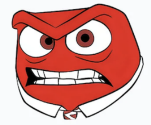

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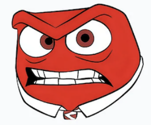

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- More meta: are we truly capturing THE essence that makes images special?


JOCKEY BOY
RESTAURANT
Coca-Cola

CHALLENGES (CONCERNS) FOR THE FIELD

- Don’t use it *just* because you can

Challenges (concerns) for the field

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  - Learn from and be transparent about your mistakes

What's next?

- AI + Generative models: scope, effect, and structure
- Technical concerns of generative models: overall opaqueness
- New developments and complex questions
- Beyond prediction: interpretation, diagnosis, and inference

WHAT'S NEXT? AI + GENERATIVE MODELS

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The scene from a Kamala Harris and Tim Walz rally in Detroit on Aug. 7. Former President Donald Trump falsely claimed that another picture of the rally showing a large crowd was generated by artificial intelligence.
Tamara Keith/NPR

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WHAT'S NEXT? AI + GENERATIVE MODELS (TECHNICAL), CONT.

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Caption: "A pro-Palestinian encampment at the University of California, Los Angeles, in April 2024."

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Caption: "A pro-Palestinian encampment at the University of California, Los Angeles, in April 2024."

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- Results and suitability for the real world: romanticization of political events

Query: "Georgia State Patrol officers detaining a protester on the Emory University campus in Atlanta on Thursday."

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What's next? Other issues

- New developments and complex questions
  - Multi-modality
  - Videos taken seriously!
- Beyond prediction
  - ML + Causal Inference → Images as treatments, outcomes...(*)
  - Stats approach to ML: Interpretable CV
  - Mixed methods approach: qual + quant

Thank you!

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