NCI Multilevel Geospatial and Contextual Webinar Series: Emerging Methods of Exploring the Team Microenvironment in Cancer Care



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# Webinar Overview

Emerging Methods of Exploring the Team Microenvironment in Cancer Care





# Towards a Social Data Science for Safety and Quality

**Emerging Methods of Exploring the Team Microenvironment** in Cancer Care

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October 9<sup>th</sup>, 2019

## Acknowledgements

#### **Collaborators**

- Hopkins (short list)
  - Salar Khaleghzadegan, Adam Sapirstein, Eileen Kasda, Carey Priebe, Mary Catherine Beach
- Rice
  - Ed Salas, Julie Dinh, Jensine Paoletti, Fred Osawald

#### **Funders**







# Agenda

- Measuring the team microenvironment
  - Definitions of key concepts
  - Social Data Science Methods
- Representative projects
  - Individual and team workload, stress, and resilience
  - Shared decision making, respect and dignity
  - Coordination in Multi-Team Systems
  - Event-reporting, narrative dynamics, and local safety climate
- Future directions

# Measuring the Team Microenvironment

Definitions, challenges, and methods



# Teams, health system delivery, and social data science (SDS)

- The quality of teamwork impacts overall safety and quality of healthcare delivery systems<sup>1</sup>
- The *team microenvironment* is... "the collection of factors that exert influence on the social interactions of people participating in care delivery."<sup>2</sup>
- Social data science (or computational social science) blends approaches for generating insights from large structured and unstructured data sets with theories of human behavior and social interactions at multiple scales.

You can learn a lot about a team without asking members questions or directly observing them: Four key unobtrusive measurement domains









Linguistic Communication

#### Paralinguistic Communication

Physiological Dynamics **Activity Tracking** 

# What team members say matters: Representative findings for linguistic analysis in teams



Linguistic Communication

Measure type	Example metrics associated with team performance
Domain specific content	<ul> <li>50+ years of team and group communication research</li> </ul>
Non-domain specific content	<ul> <li>The frequency of positive, assenting words vs dissenting words, the positive emotion words, use of first person plural, lower variability in word count across team members are positively associated with task performance outcomes<sup>1,2</sup></li> </ul>
Similarity in word use	<ul> <li>Task related linguistic alignment predicts team task outcomes<sup>3</sup></li> <li>Linguistic style matching predicts affective and task outcomes<sup>4</sup></li> <li>Overall semantic similarity predicts task outcomes<sup>5</sup></li> </ul>
Sequence in word use	<ul> <li>Closed-loop communication<sup>6</sup></li> <li>Anticipation ratio<sup>7</sup></li> </ul>

#### What team members communicate without using words matters: Representative findings for paralinguistics in teams



Paralinguistic Communication

Measure type	Example metrics associated with team performance
Communication flow	<ul> <li>Egalitarian turn taking predicts team task outcomes<sup>1.2</sup></li> <li>Lower stability in turn taking sequence predicts team task outcomes<sup>3</sup></li> <li>Speech duration predicts perceptions of emergent leadership <sup>4</sup></li> </ul>
Facial expression and gaze behavior	<ul> <li>Synchrony in facial expressions positively predicts team affective and task outcomes<sup>5,6</sup></li> <li>Low synchrony in facial expressions predicts performance strategy shift<sup>6</sup></li> <li>Synchrony in gaze behavior predicts team task outcomes<sup>7</sup></li> </ul>
Vocal features	<ul> <li>Large feature space models are predictive of individual affective states, personality, and perceptions of competence in persuasiveness<sup>8</sup></li> </ul>
Gesture and posture	<ul> <li>Synchrony in postural sway negatively predicts team affective outomes<sup>9</sup></li> </ul>

### The physiological dynamics of interacting team members matter: Representative findings for physiological dynamics in teams



Physiological Dynamics

Phys.	Inputs	Mediators	Outputs
EEG/ fNIRS	<b>Mixed findings</b> : PS higher in competitive vs. cooperative tasks <sup>7</sup> ; higher for expert (vs. novice) teams <sup>20</sup> . EEG shows PS increases with task demands <sup>24,26,29</sup> and task uncertainty <sup>7,25</sup> but fNIRS shows reduced PS with increased task demands <sup>21</sup> .	<b>Limited findings</b> : Non-linear 'flexibility' associated with more terse domain-specific communication <sup>7</sup> .	No findings
EMG	<b>Many factors</b> : Liner PS in smiling and frowning higher in competitive vs. cooperative tasks <sup>9</sup> , with gender differences <sup>11</sup> . PA higher for lower expertise team members <sup>26</sup> .	<b>Mixed findings</b> : Linear PS in facial EMG not related to team affective states <sup>17</sup> , but higher non-linear PS was associated with higher negative emotions in the team <sup>23</sup> .	<b>Limited findings</b> : Non-linear (but not linear) PS in postural sway positively predicts affective outcomes <sup>15</sup> .
Electro- dermal	<b>Many factors</b> : No effect of composition (gender <sup>11</sup> , inclusion of synthetic agent <sup>10</sup> ) on linear PS. Higher PA in cooperative vs. competitive tasks, with gender differences <sup>28</sup> . Trait anxiety and empathy impacts linear and non-linear PS <sup>21</sup> .	<b>Mixed findings</b> : Non-linear PS negatively associated with leadership behaviors <sup>22</sup> , but positively associated with positive affective states <sup>23</sup> .	<b>Consistent findings</b> : Linear PS positively predicted team task <sup>1,13</sup> and affective <sup>5</sup> outcomes.
Cardio- vascular	<b>Many factors</b> : Linear PS is higher in competitive vs. cooperative tasks <sup>5</sup> , varying with team composition (higher PS in males <sup>11</sup> , lower with inclusion of synthetic agent <sup>10</sup> , PA decreases with increasing expertise <sup>26</sup> ). Linear PS increases with task difficulty <sup>13</sup> .	<b>Mixed findings</b> : Linear <sup>4</sup> PS was negatively associated with team process measures, while non-linear PS was both negatively <sup>15</sup> and positively <sup>19</sup> associated with team process.	<b>Mixed findings</b> : Across studies linear PS both positively <sup>1,2,3,17</sup> and negatively <sup>4</sup> predicted team task outcomes, while PA negatively predicted task outcomes <sup>9</sup> . Linear <sup>5</sup> and non-linear <sup>15</sup> PS negatively predicted affective outcomes.

Kazi S, Khaleghzadegan S, Dinh JV, Shelhamer MJ, Sapirstein A, Goeddel LA, Chime NO, Salas E, Rosen MA. Team Physiological Dynamics: A Critical Review. Human factors. 2019 Sep 26:0018720819874160.



Where team members are and what they are doing matter Examples of activity tracking

Activity Tracking

- Co-location networks for measures of team risks<sup>1</sup>
- Electronic health record access logs for measures of workload<sup>2</sup> and team coordination<sup>3</sup>
- Wearables for physical work process mapping<sup>4</sup>
- Administrative data for mapping patient paths through healthcare delivery system<sup>5</sup>

# How are these measures applied?

Торіс	Study	Linguistic	Paralinguistic	TPD	Activity Tracking
Individual and Team Workload, Stress and Resilience	Nursing workload in the ICU	-	Y	-	Y
	Internal Medicine Resident Work	-	-	-	Y
	Collective allostatic load in a PICU	-	Y	Y	Y
	Teamwork competency assessment	Y	Y	Y	Y
Shared decision making, respect and dignity	ECHO	Y	Y	-	-
Coordination and MTSs	Handoffs and teamwork across units in an acute care facility	-	-	-	Y
Climate and narrative dynamics	Event reporting and the language of blame	Y	-	-	-

# Individual and Team Workload, Stress and Resilience

# Challenges with individual and team workload and it's measurement

- Workload is related to:
  - Patient outcomes
    - Patient experience
    - HAIs
    - Delays in treatment
    - Postop complications
  - Workforce and organizational outcomes
    - Burnout and job dissatisfaction
    - Turnover, disengagement from or exiting the professions
    - Efficiency and productivity

- Existing approaches to measuring workload rely on:
  - Staffing ratios (sometimes weighted by acuity systems)
  - Observation
  - Survey

# Study 1: RN workload in an ICU

### GORDON AND BETTY MOORE FOUNDATION



#### **Patient Factors:**

- Level of care
- Insulin drip
- Vent.
- Vasoactive
- PA cath
- CVVHD
- Flap or spine checks



## Study 1: RN workload in an ICU

### GORDON AND BETTY MOORE FOUNDATION

+	PI: Michael F	losen; Study #: IRB00028389; Study Name	: Sensor-based workflow analysis: A Pilot Study
		PART 1—To complete at the BEGINNING	G of your shift
	Today's date:	Scheduld shift start time:	End time:
	What is the number on your ser	nsor badge?:	

#### Part 2—Complete at the END of your shift





#### **Shift factors:**

- *#* of patients
- Composite of # of patients by task
  - factors
- CNA?
- When rounding occurred



### Study 1: RN workload in an ICU

### GORDON AND BETTY MOORE FOUNDATION

+	PI: Michael Rosen; Stu	udy #: IRB00028389; Study Name: Sensor-b	ased workflow analysis: A Pilot Study
	PART 1	—To complete at the BEGINNING of your s	hift
	Today's date: S	Scheduld shift start time:	End time:
	What is the number on your sensor badg	ge?:	

#### Part 2—Complete at the END of your shift

How many patients were you assigned today?:

Pati	ent 1	Pati	ent 2	Pati	ent 3	Pati	ent 4
Room #:		Room #:		Room #:		Room #:	
Level: CU CU C	IMC 🗆 PCU 🗅	Level: CUC I	MC PCU 🛛	Level: CU CU C	IMC 🗆 PCU 🗅	Level: CUC ICUC I	MC PCU n
Insulin	PA cath	Insulin	PA cath	Insulin	PA cath	Insulin	PA cath
drip		drip		drip		drip	
Ventilator	CVVHD	Ventilator	CVVHD	Ventilator	CVVHD	Ventilator	CVVHD
Isolation	Checks:	Isolation	Checks:	Isolation	Checks:	Isolation	Checks:
Observer	🗆 Flap	Observer	🗆 Flap	Observer	🗆 Flap	Observer	Flap
Vasoactive	Spinal	Vasoactive	Spinal	Vasoactive	Spinal	Vasoactive	Spinal

#### Please indicate by marking on the timline: when did you have a tech today? Or check:



#### Self-report exertion:

• Q 4 hr ratings of mental and physical exertion



#### Example metric set for RN workflow

Time in location Movement through space Transitions between areas (#) 'Burstiness' of transitions Shannon Entropy of locations over time Audio Volume (mean, sd) Pitch (mean, sd) Time spent speaking 'Burstiness' of speaking Accelerometer and gyroscope metrics Activity (energy) level Body movement Time standing / sitting Time walking 'Burstiness' of walking Location x (Audio & Accel./gyro. Measures)



#### **RN** Workstation

• 3 stations ea.

Service Areas

- Med rm
- Supply rm
- Nutrition

Patient Rooms

- 2 sensor ea.
- 4 rms excluded

All else = "off the grid"

• Unaccounted for time

Rosen MA, Dietz AS, Lee N, Wang IJ, Markowitz J, Wyskie RM, Yang T, Priebe CE, Sapirstein A, Gurses AP, Pronovost PJ. Sensor-based measurement of critical care nursing workload. PloS one. 2018 Oct 12;13(10):e0204819.



## GORDON AND BETTY MOORE FOUNDATION

### Analysis process

#### Dataset

- 356 work hours from 89 4-hour blocks across 35 shifts
- Dimension reduction
  - Elastic net method applied to 72 sensor features (plus pairwise interactions) for each outcome
- Multi-level Modeling
  - Test grouping structure (shift)
  - Level 1 predictors (sensor features)
  - Level 2 predictors (task demands)
  - Random coefficients
  - Cross-level interactions

# Findings



Mental Ex	ertion F	hysical Exertion	~
• 63% d	<b>Overall patterns of interaction</b>	hat matter	etween shifts
	<ul> <li>Burstiness of speaking</li> </ul>		
• Final I	<ul> <li>Time speaking outside of main wo</li> </ul>	ork areas × Time at nursing	for:
• 5%	stations		iance
• 73	<ul> <li>Entropy of transitions x Burstines</li> </ul>	s of transitions	variance
• With: •	<b>Context specific interactions the</b>	at matter	
• 5 •	<ul> <li>Patient on an insulin drip X Burstin</li> </ul>	<b>less</b> of speaking	
• 1	<ul> <li>Average patient load x Volume w</li> </ul>	nile speaking at nursing	patient load)
• 10	stations		n (Avg pt load x
drip x	burstiness of speaking)	Volume speaking at RN	🖣 station)



### Study 2: Does this scale to residents?

#### Questions

How are residents spending their tim do differences pre educational or we outcomes? **Pilot overview** 43 Interns July – Oct 2018

3,973 shifts 45,367.8 hrs

#### Single sensor

Location tracking system + EHR metrics





# **Study 3: Collective Allostatic Load in a PICU**



- 1. Better understand the impact of **chronic** and **acute stressors** on **individual** and **team performance** in the PICU.
- 2. Explore how team interactions exacerbate or ameliorate these stress effects.

#### Why do this?

- Better workload measurement systems which can drive unit resource allocation decisions in near real-time
- Counter measures for staff to minimize, manage, and mend from stress effects

## **Measurement framework**



Stressors / work demands	Stress responses	Teamwork	Task and team
<u>Administrative data</u> : Measures characterizing patient cohort (census, churn, acuity scoring) and staffing levels (RN/pt ratio), and nursing activity (TISS-28, NAS)	<u>Self-reported workload</u> : NASA-TLX revised	<u>Self-reported teamwork</u> <u>quality</u> : Team process scale; Mayo High Perf. Teamwork Scale in codes	<u>Individual burnout</u> : Maslach short
<u>Self-reported stressors</u> : Custom survey capturing unique features of the work day that cause stress in the PICU	<u>Emotional state</u> <u>recognition</u> : Physiology (Cardiac and electro- dermal responses), and speech features (vocal stress)	<u>Team interaction patterns</u> : Movement and communication patterns (involving no recordings of actual speech)	<u>Team affect</u> : Mutual trust, team potency / efficacy
	- -		<u>Objective task outcomes</u> : Call button response latencies; CPR quality

scores in codes



# Study devices, and why we are using them



Staff location badge

Movement and Physical Workload



Wrist worn physiology monitor

Workload and stress measurement



# Data collection overview: A day in the life of the study



**1.** Focus is on PICU Leadership Team (Fellows and Charge Nurses).

2. We need a whole team to collect data!





# **Study 4: Sociometric Team Selection Project**

- Generate construct and criterion validity evidence for individual and team LDSE behavioral competencies.
- Develop unobtrusive and sociometric indices of individual and team LDSE behavioral competencies.
- Develop technology and guidelines for the use of sociometric measures in astronaut selection.



# Coordination and Multi-team Systems

# Example Handoff Improvement Research (resident to resident)

- Resident handoff-improvement program in 9 sites
  - 23% decrease in medical error rate
  - 30% decrease in preventable adverse event rate
  - No change in non-preventable adverse event rate
  - Significant increase in inclusion of key handoff elements (verbal and written)
  - No significant change in handoff duration (2.4 to 2.5 minutes per patient), or resident workflow, patient-family contact, or computer time.

Starmer, et al. "Changes in medical errors after implementation of a handoff program." *New England Journal of Medicine* 371, no. 19 (2014): 1803-1812.

The NEW ENGLAND JOURNAL of MEDICINE

SPECIAL ARTICLE

#### Changes in Medical Errors after Implementation of a Handoff Program

A.J. Starmer, N.D. Spector, R. Srivastava, D.C. West, G. Rosenbluth, A.D. Allen, E.L. Noble, L.L. Tse, A.K. Dalal, C.A. Keohane, S.R. Lipsitz, J.M. Rothschild, M.F. Wien, C.S. Yoon, K.R. Zigmont, K.M. Wilson, J.K. O'Toole, L.G. Solan, M. Aylor, Z. Bismilla, M. Coffey, S. Mahant, R.L. Blankenburg, L.A. Destino, J.L. Everhart, S.J. Patel, J.F. Bale, Jr., J.B. Spackman, A.T. Stevenson, S. Calaman, F.S. Cole, D.F. Balmer, J.H. Hepps, J.O. Lopreiato, C.E. Yu, T.C. Sectish, and C.P. Landrigan, for the I-PASS Study Group\*

#### Study 5: Inter-unit patient transfers 1 FQ / ~12k pt admissions / ~ 1,000 bed hosp. / 108 units



#### Study 5: Data and Analysis

#### **Traditional unit metrics**

• Bed size, 'churn', LOS

#### **Temporal features of transitions**

- # in AM/PM, wkdy/wknd
- 'Burstiness' in AM/PM, wkdy/wknd

#### **Structural features of transitions**

 In/out degree, centrality, betweenness, density, transitivity

#### Teamwork Across Hospital Units (TAHU)

- Hospital units do not coordinate well with each other. [R]
- There is good cooperation among hospital units that need to work together.
- It is often unpleasant to work with staff from other hospital units. [R]
- Hospital units work well together to provide the best care for patients.

### Study 5: Findings (43 Units from one hospital)

Predictor	β (SE)	t (p)
Betweenness Centrality (weighted)	0.40 (0.13)	3.0 (0.005)
Discharge Burstiness during Night Shift	0.27 (0.14)	2.0 (0.056)
Average Neighbor Degree	0.24 (0.14)	1.8 (0.086)
Adj R <sup>2</sup> = 0.23 F(3,39) = 5.08 p = 0.005		

Patient safety event reporting, unit climate, and narrative dynamics

#### Challenges in patient safety event reporting



### Study 6: Are there better ways?

- Apply topic modeling to safety event reports
- Explore <u>content validity</u>
  - Can we find coherent patterns? Of important safety trends?
  - How well are discovered patterns currently represented in event taxonomies?
- Explore predictive validity
  - Do topic scores account for variance in harm scores above and beyond existing event categories?

#### Topic Modeling with LDA Example



## Study 6: Approach

- Topic modeling
  - 13,317 reports from over 15 months
  - 40 topic model was 'best fitting'
- Topic labeling and rating
  - Review by 5 SMEs in 9 hours of focus groups
  - Ratings of coherence, importance, and current awareness / representation in event taxonomies
- Multi-level modeling of harm scores
  - Existing event categories used as grouping variable, and predict within and between group variance in harm scores

# Study 6: Example Topics

Topic 1 Blood Blood Products Request Unit Product Bank	Topic 2 Infus Heparin Rate Drip Weight CPN Start Heparin or	Topic 3 Bed Floor Falls Fell Bathroom Sit Head	Topic 4 Pressur Unable Bleed Continu Would Eval Elev	Topic 5 Chang Shift Pain Errors at time of shift Day Everi
Sent	High Risk	Chair	Ulcers or	High
Transfus	Meds	Side	Wound Care	Dilaudid

40

#### Study 6: Results

# The majority of topics (72.5%) were rated as highly coherent, and only 5% were rated as having no discernable pattern

1: Risky env. Conditions	2: Comm. / coord. Breakdowns	<mark>3</mark> : Skin damage	4: Retained foreign object
patient, room, left, safety, enter	call, told, state, get, take	site, arm, right, left, assess	xray, needl, chest, count, case
<mark>5</mark> : Patient ID	6: PCA use error catches	7: Blood product management	8: Specimen management
name, discharge, home, patient, mother	chang, shift, pain, night, pca	blood, red, cell, return, request	lab, result, drawn, draw, test
9: Interpersonal conflict	<mark>10</mark> : No pattern	11: Line placement / mngmnt.	12: Equipment contamination
ask, said, put, know, want	back, one, came, still, come	line, central, cathet, place, babi	tray, set, clean, steril, instrument
<mark>13</mark> : Code issues	14: Ambig. or incorrect orders	15: Orders and patient ID	16: Medication errors
bedsid, assess, immedi, vital, code	given, patient, review, chart, notifi	note, upon, document, may, follow	medic, pharmacy, med, dose, administ
17: Med labeling error	18: Pt transfer issues	19: Specimen labeling	20: Patient aggression
check, correct, label, doubl, wrong	patient, admit, transfer, floor, admiss	specimen, contain, locat, receiv, must	staff, secur, member, family, leav
21: No pattern	22: Access to services	23: Allergic reaction to contrast	24: Med order/dosing errors
use, anoth, make, complet, sure	care, provid, contact, clinic, today	mri, contrast, scan, inject, patient	order, dose, poe, receiv, enter
<mark>25</mark> : Falls	26: controlled substance waste	27: Blood sugar / insulin mngmt	28: Distributed comm.
bed, floor, assist, fall, fell	wast, found, fentanyl, drop, pyxi	pts, blood, insulin, glucose, check	Page, pacu, resid, anesthesia, servic
29: Missing wrist band	30: Patient consent	31: Pt transfer w/o monitoring	32: Infusion pump & tubing
patient, caus, wristband, must, phlebotomist	report, place, prior, without, consent	arriv, unit, charg, transport, notifi	tube, pump, bag, fluid, run
33: Com. & role clarity	34: Dental and equip issues	35: Pressure ulcers and BP	36: Airway management
team, communic, picu, attend, plan	procedur, remov, attempt, pull, area	pressur, unabl, bleed, continu, wound	equip, machine, oxygen, intub, sedat
37: Transitions of care	38: Scheduling / coord. Issues	39: Med infusion errors	40: Med error – discrepancy
nurs, inform, made, receiv, awar	time, need, hour, due, avail	infus, heparin, rate, drip, weight	day, number, system, record, occur

Table 2. Topic names and top 5 words for a 40 topic model of PSER data. Green = topics rated as highly coherent; Yellow = topics rates as somewhat coherent; Red = Topics rated as incoherent.

# Topic coherence and importance by awareness and representation (examples)

		Current awareness and representation in event taxonomy	
		High	Low
Topic <u>coherence</u> and <u>importance</u>	High	<ul> <li><u>11 topics</u></li> <li>OR controlled substances waste management</li> <li>ID/safety bands not scan-able</li> <li>Blood wastage</li> <li></li> </ul>	<ul> <li><u>14 topics</u></li> <li>Central lines</li> <li>Hypoglycemia events</li> <li>Pre-procedure issues</li> <li>Dose monitoring errors</li> <li></li> </ul>
	Low	<u>O topics</u>	<ul> <li><u>15 topics</u></li> <li>Logistics and operational barriers</li> <li>Electronic ordering configuration</li> <li>Extubations</li> <li>Availability of resources</li> <li></li> </ul>

#### Topics vs. PSN Event Types

- Heatmap Proportion of events within PSN category classified into each topic
- One to one mapping ٠ (telling what we already know)
- Some join or split ٠ categories (new way to think about what we already know)
- Some have no clear correspondence (new pattern)



ñ

**Topic Label** 

Der

õ

Line

# **Study 6: Takeaways**

#### **Findings**

- Existing event categories as a grouping variable
  - 51% of variance was between event categories
  - 49% of variance was within event categories
- Lexical features (sentiment analysis, LIWC)
  - 11% of between event variance
  - 3% of within event variance
- Topic scores
  - 27% of between event variance
  - 6% of within event variance

#### **Future directions**

- Language of blame in event reporting data as a marker of local climate
  - Natural experiment around a just culture implementation
- Towards measures of narrative stability and change as makers of climate

Summary of social data science (SDS) pilot studies: Describe, explain, predict, control

- SDS methods are useful for **description** and strong in **prediction** 
  - The detail can be overwhelming, and requires engaging domain experts with complex data
  - Highly predictive, but poorly explanatory models are of limited interest
- SDS needs tighter coupling with social sciences to enable explanation
  - Ongoing process of applying, adapting, and building new theory
  - New methods enable more temporal theories of social interaction
- We've only scratch the surface of interventions for **control** 
  - Better systems for selection, training and development, ongoing support, and operations management

# Future directions for Social Data Science

#### SDS can enable translational organizational sciences.

#### **Better science**

- Reduced burden of data collection
- Increased scale of data collection
- Multi-method triangulation

#### **Better organizations**

- Selection systems
- Work redesign
- Risk monitoring
- Performance feedback

# Thoughts on the road ahead

- Need to mature integrative frameworks
  - Huge variety in theories and methods available
- Need to invest in fundamental measure validation
  - What is an appropriate approach to scaling measures up
- Need to build the technical infrastructure
  - Current investments focus on clinical data (correctly), but do not include key SDS data sources (e.g., EHR access logs)
- Need to invest in the human capital
  - Introducing into
  - Brining strong research teams together
  - Best configurations of SDS skill sets across team members

#### Thanks for your time. Questions?

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#### www.cancer.gov

www.cancer.gov/espanol