vs. anti-inflammatory/pro-resolving) helps determine the magnitude of the interferon signature. In addition to reflecting IFN-I production, the interferon signature critically depends on the Nrf2-regulated responsiveness of macrophages to signaling through the IFNAR. These studies provide a new perspective on the interferon signature that may have implications for understanding the pathogenesis of lupus. In addition, these studies suggest that Nrf2 activators could have a role in the therapy of lupus.

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APPLICATION OF TEXT MINING METHODS TO IDENTIFY LUPUS NEPHRITIS FROM ELECTRONIC HEALTH RECORDS

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Background Lupus nephritis (LN), or chronic inflammation of the kidneys, is a frequent complication of SLE and associated with higher overall morbidity and mortality. Previous studies have found that LN affects individuals of Hispanic, African American and Asian descent more than those of European ancestry. Accurate estimates of LN in the population remain limited due to the inability to capture this information through structured data fields in electronic health records (EHRs). We aimed to develop a text mining pipeline to extract information on LN diagnosis within clinical notes in the EHR of a large, diverse university health system.

Methods Individuals with a single diagnosis code for SLE (710.0) during June 1, 2012–November 5, 2016 from the EHR of a university health system were included (n=2,509). All clinical notes for patients were extracted and annotated using a clinical text-mining tool, the Clinical Event Recognizer (CLEVER), and a custom-built dictionary that included lupus nephritis and associated terms. Positive and negative mentions of LN were tagged and evaluated for performance.

Results Over 1300 positive and 400 negative mentions of LN were detected from clinical notes. Manual review of 50 note mentions (25 positive and 25 negative) determined that our text-mining tool detected LN with 79% sensitivity and 86% specificity (table).

Conclusions We conducted the first text-mining strategy to extract LN status from clinical notes. Additional evaluation of the LN text-mining pipeline on a gold-standard chart-reviewed cohort of SLE patients (n=332) is ongoing. Further refinement of the pipeline will allow us to classify stage of LN (Class I-IV) to better phenotype SLE severity, and conduct

Abstract 187 Table 1 Number of positive and negative mentions of lupus nephritis identified through the text-mining tool and manual review.

Text-Mining Tool	Manual Review	
	Positive	Negative
Positive	22	3
Negative	6	19
Total:	28	22

follow-up studies to determine factors associated with this important disease outcome.

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VALIDATION OF AN ADMINISTRATIVE ALGORITHM TO ASSESS SLE DISEASE SEVERITY

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Background SLE severity is heterogeneous: some patients have mild disease with rashes and arthritis, while others have severe multi-organ system involvement. It is challenging to study SLE in administrative databases given this heterogeneity. Garriss et al developed an administrative claims-based SLE severity algorithm derived from elements of the SLEDAI, SLAM and BILAG instruments (Garriss, J Med Econ 2013). It employs ICD-9, CPT and NDC claims over a 1 year period and classifies patients as having mild, moderate or severe disease. We sought to validate this administrative algorithm in comparison to SLEDAI scores at clinical visits.

Methods We identified 100 SLE patients followed at the Brigham and Women's Hospital (BWH) Lupus Center (2008–2010) with SLEDAI-2K (Gladman, J Rheumatol 2002) data at each visit over a 1 year period per person. We also obtained ICD-9, CPT and NDC codes for the Garriss algorithm items (e.g. codes for glucocorticoids, ICD-9 codes for pericarditis) for the same year per subject. We compared Garriss SLE severity to the highest SLEDAI-2K in that year. We defined the SLEDAI-2K categories of mild <3, moderate 3–6, and severe >6 as in the literature (Polachek, Arthritis Care Res 2017). We compared classification in binary categories of mild vs. moderate/severe and mild/moderate vs. severe. For each, we calculated sensitivity, specificity, and C-statistics.

Results We analyzed 377 SLEDAI-2K assessments on 100 subjects (mean 3.77 [SD 2.63]) in the BWH Lupus Cohort. For the Garriss vs. highest SLEDAI-2K model, 56 of 100 subjects were classified similarly by Garriss and highest SLEDAI-2K (23/36 mild, 22/34 moderate, and 11/36 severe by SLEDAI-2K). The performance characteristics compared to the highest SLEDAI-2K of the year were: C-statistics were 0.755 for mild/moderate vs. severe SLE severity and 0.740 for mild vs. moderate/severe (table). Sensitivity of the Garriss algorithm compared to the highest SLEDAI-2K were 63.9% for mild vs. moderate/severe and 94.3% for mild/moderate vs. severe.

Abstract 188 Table 1 Garriss administrative algorithm for SLE severity vs. highest SLEDAI-2K

	Highest SLEDAI-2K	
	Mild vs. Moderate/ Severe	Mild/Moderate vs. Severe
Sensitivity	63.9%	94.3%
Specificity	82.8%	36.7%
C-statistic	0.740	0.755