**Supplementary Figure S1: Location of surgical resection, post-surgical, outcome and simulated seizure likelihood.**



**Supplementary Figure S1: Location of surgical resection, post-surgical outcome, and simulated seizure likelihood.** Further to the two exemplary cases shown in Fig. 4, fourteen more cases are shown here. P3 to P9 correspond to cases in which patients were rendered

seizure free, while for cases P10 to P16, seizures persisted post-surgery. Electrodes in black indicate the location of surgical resection, whereas the color plot represents computed seizure likelihood for different cortical regions.

**Supplementary Figure S2: Consistency across different inter-ictal segment and frequency bands.**



**Figure S2a: Different inter-ictal segments**



**Figure S2b: Different frequency bands**

### **Supplementary Figure S2: Consistency across different inter-ictal segments and frequency**

**bands**. The upper panel depicts the distribution of seizure likelihood for different inter-ictal

segments. For patient P1 the availability of inter-ictal data was constrained to one hour. Consequently, we limited the epoch segments to 15min duration. Patient P2 underwent two days of intracranial investigation; the first 1-hour epoch segment has been selected from the beginning of monitoring and the other two epochs are chosen from different days. The lower panel illustrates the distribution of seizure likelihood for  $\theta$ ,  $\alpha$ ,  $\beta$ ,  $\gamma$  frequency bands and a frequency band from 70-150 Hz. The escape time depends on the frequency band but the distribution of seizure likelihood remains unaffected. Therefore, it is not necessary to choose specific frequency bands in order to make predictions.



**Supplementary Figure S3: Raw ECoG signals from randomly chosen electrodes.**

**Supplementary Figure S3: Raw ECoG signals from randomly chosen electrodes.** Panel (a) shows four randomly chosen electrodes from the ECoG grid of patient P1 and P2. The ECoG signals are shown at a resolution of 10min, 10s and 5s. It is apparent that there is no unusual difference between the raw inter-ictal signals from the electrodes placed at

different locations on the cortex.





**Figure S4(a): Subject P3 to P9**

Prior

Random

Actual



### **Figure S4(b): Subject P10 to P16**

**Supplementary Figure S4: Prediction of surgical outcomes by simulating resections.** This

figure illustrates the prediction of surgical outcomes for fourteen more patients; it is the equivalent of Fig. 5 where the same is shown for two exemplary cases. In each case, we have removed the nodes within the resected cortical tissues from the model. We compared the consequent increase in escape time with that of the random node removals and made predictions which are mentioned corresponding to each patient.



#### **Supplementary Figure S5: Receiver operator characteristic analysis**

**Supplementary Figure S5: Receiver operator characteristic analysis.** Receiver operating characteristic for the prediction of good and bad surgical outcomes using difference in escape time and *d-score* as a classification feature. The threshold value for optimal classification is indicated in both the figures and the black dot denotes the point with best classification which is the point closest to (true positive rate = 1, false positive rate = 0). Abbreviation: Sens.– sensitivity, Spec.– specificity, Acc.– accuracy, AUC– area under the curve, Thres.– threshold for classification.



### **Supplementary Figure S6: Exploration of alternative resection strategies.**

**Figure S6(a): Subject P3 to P8**



**Figure S6(b): Subject P9 to P14**



### **Figure S6(c): Subject P15 to P16**

## **Supplementary Figure S6: Exploration of alternative resection strategies.** This figure

depicts the *in silico* approach we propose for the exploration of different surgical options. It is the equivalent of Fig. 6 for fourteen additional cases. For each case, we compute the set of nodes with highest seizure likelihood which are shaded in black. The box plot represents the increase in escape time upon removal of these nodes compared against the removal of random nodes from the model.

# **Supplementary Text S7: Additional information about the patients provided by the**

## **IEEG portal.**

The details of following patients used in this study have been adapted from the IEEG portal. Further details on these patients can be found at [https://www.ieeg.org](https://www.ieeg.org/)































**Subject P15**







**Supplementary Text S8: Applying Laplacian and Bipolar montage for ECoG preprocessing.**

### **1. Laplacian Montage**



**Figure S8.1:** Illustration of simulated seizure likelihood for the two exemplary subjects (P1 and P2) when Laplacian montage was applied for pre-processing ECoG signals. In the left panel, for subject P1, the cortical locations with highest seizure likelihood, as depicted by the red areas on the colour plot, are scattered in multiple areas. This is also the case for Subject P2 in the right panel suggesting little to no benefit to use of a laplacian montage.

Laplacian montage refers the signal from an electrode to the signals from its nearest neighbouring electrodes (Lagerlund 2000). An electrode may be surrounded by either four, three or two neighbouring electrodes, depending on whether it is located on the centre, edge or corner of an electrode grid. Similarly, an electrode on the strip will have either two or one neighbouring electrode depending on whether it is located on the middle or at the edge of the strip electrode. In general, let us assume that an electrode channel  $E$  has  $n$  nearest neighbours denoted by  $(E_1, E_2, ..., E_n)$ . We applied Laplace montage on E to obtain  $E_l$  as follows:

$$
E_l = E - \frac{1}{n} (E_1 + E_2 + \dots + E_n)
$$

While keeping all other pre-processing steps same as described in Section 2.2, we obtained a functional network from the ECoG signals corresponding to each subject. We incorporated this network in the model and computed simulated seizure likelihood as described in section 2.2 and 2.3. The distribution of simulated seizure likelihood are colour coded in the above figure for the two exemplary subjects P1 and P2.

### **2. Bipolar Montage**



Figure S8.2: Illustration of simulated seizure likelihood for the two exemplary subjects (P1 and P2) when longitudinal and transverse bipolar montage, in the right and left panel respectively, were applied for pre-processing ECoG signals. Note that the regions with highest simulated seizure likelihood, colour coded in red, are in the same cortical locations as in Figure 3. Specifically, for patient P1, the surgical areas diagnosed clinically, correlates with the regions with high simulated seizure likelihood in the right temporal lobe. On the other hand, for patient P2, the regions with highest seizure likelihood are clearly distinct from the clinically diagnosed surgical region in the left parietal cortex.

Bipolar montage approximates the spatial derivative of potential fields by subtracting the potentials measured at adjacent locations (Zaveri et al. 2016). For intracranial electrode grids, the difference between the potential may be obtained by referring each electrode to its adjacent electrode in either longitudinal or transverse direction. For the strip electrodes, bipolar montage can be applied by referring each electrode to its adjacent electrode.

We applied the bipolar reference in both longitudinal and transverse direction which are depicted by the arrows on the electrode grids in Fig. S8.2. We kept all other pre-processing steps the same as in Section 2.2 and obtained functional network from the ECoG signals. This functional network was incorporated in the model to compute seizure likelihood distribution as detailed in section 2.2 and 2.3. As evident from Fig. S8.2, the cortical areas with high simulated seizure likelihood (shown in red) are in agreement with Figure 3.

### **Reference:**

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**Supplementary Text S9: Estimating asymmetric network by applying Kullback-Leibler divergence.**



Figure S9. Illustration of simulated seizure likelihood distribution for Subject P1 (on the left) and P2 (on the right) computed by incorporating an asymmetric connectivity parameter in the model. The asymmetric connectivity was obtained from the ECoG signals by applying Kullback-Leibler divergence. Note that the cortical areas with high simulated seizure likelihood (shown in red) are in the same locations as those shown in Fig. 4, where we simulated the model with a symmetric connectivity parameter.

Kullback-Leibler divergence is an information-theoretic interdependence measure, which quantifies the dissimilarity (or distance) between two random variables (or signals). We computed the normalized spectrogram of a signal,  $x(n)$ , as follows:

$$
W_x(n,f) = \frac{|X(n,f)|^2}{\sum_{n,f} |X(n,f)|^2}
$$

where,  $X(n, f)$  is the Short-time Fourier transform of  $x(n)$ , obtained using a Hamming window of 1s duration, with 50% overlap between the contiguous sections. The summation in the denominator was carried out over all the time windows and frequency range of 1 to 70Hz. We treated the normalized spectrograms as probability distributions and incorporated them in the Kullback-Leibler divergence equation:

$$
K\big(W_x, W_y\big) = \sum_{n,f} W_x(n,f) \log \frac{W_x(n,f)}{W_y(n,f)}
$$

Kullback-Leibler divergence is an asymmetric measure; it diverges when the distributions are disjoint. Therefore, higher values of  $K(W_x, W_y)$  denotes greater dissimilarity (or distance) between the signals and vice-versa. Accordingly, we computed the model connectivity

<b>Subjects</b>	<b>Actual</b> <b>Outcome</b>	<b>Actual resection vs Random Resection</b>	
		$t_{(\text{act-random})}$	Cohen's D
<b>P1</b>	Good	1.717991	0.163534
P <sub>2</sub>	<b>Bad</b>	$-11.605394$	$-0.270335$
<b>P3</b>	Good	-3.875874	$-1.635309$
<b>P4</b>	Good	2.453177	0.265004
<b>P5</b>	Good	$-0.401350$	$-0.042630$
<b>P6</b>	Good	11.702740	0.507963
P7	Good	$-26.264418$	-2.527758
P <sub>8</sub>	Good	0.680521	0.200424
P <sub>9</sub>	Good	$-4.044922$	$-0.197963$
<b>P10</b>	<b>Bad</b>	$-0.825498$	$-0.078635$
<b>P11</b>	<b>Bad</b>	1.463651	0.082652
<b>P12</b>	<b>Bad</b>	11.659090	3.722591
<b>P13</b>	<b>Bad</b>	25.742838	1.064707
P <sub>14</sub>	<b>Bad</b>	4.992155	0.359724
<b>P15</b>	<b>Bad</b>	$-17.463871$	$-1.214751$
P <sub>16</sub>	<b>Bad</b>	12.906590	2.538486

parameter  $C$ , which relates similar signals with higher weights, by obtaining the inverse of  $K$ , followed by its normalization between 0 and 1.



#### **Supplementary Text S10: Alternative network measures.**

We consider the elipeptogenicity model (equation 3) as a way of measuring a property of the (functional) network that underpins it, since all other parameters besides the network are homogeneous and the same for all patients. Here we investigate how the model output correlates with other measures of properties of the functional networks. In recent years, graph theory has emerged as a useful way of measuring other properties of brain networks.

Many measures of local (nodal) properties exist and reflect different aspects of the node's role in the network. For example, the **clustering coefficient** (CC) measures the interconnedtedness of the neighbours of a node. This means that nodes with a high clustering coefficient are connected to nodes which are highly (rather than rarely) connected to each other. The **betweenness centrality** (BetC) of a node measures how many times the node occurs in the shortest path between other nodes. Those nodes with a high betweenness centrality are often considered as hubs in the network. Node **strength** (Str) is simply the sum of connection strengths with all other nodes. Nodes with a medium value for strength may be connected to few other nodes very strongly, or many nodes fairly weakly – hence making interpretation more difficult. For this reason, many studies analyse the node degree (simply the number of other nodes which are connected) by arbitrarily thresholding the network to make it sparse. For brevity we do not investigate node degree here though, since the thresholding discards information. Finally, the **eigenvector centrality** (EigC) is another way to determine 'hub' nodes, and is similar to the Google PageRank algorithm. Nodes have a high eigenvector centrality if they are strongly connected to other nodes which are also central to the network (Lohmann *et al.* 2010). Formal descriptions of all of these network measures can be found in (Rubinov & Sporns, 2010; Kaiser, 2011; Lohmann *et al.* 2010). Many other network measures also exist to describe global (as opposed to local) properties of the network. However, we restrict our analysis here to local measures only since we are interested in local properties of the network for surgery localisation. We also limit ourselves to these four measures which have been used primarily in the field before (e.g. Wilke *et al.*, 2011; Hutchings *et al.*, 2015) and an extensive comparison of all measures is beyond the scope of this work.

To investigate the utility of these other measures we used routines implemented in the Brain Connectivity Toolbox in Matlab. We measured the local properties of the nodes in the random-surgery and actual-surgery networks to generate two distributions of each measure, in each subject. The random node surgical distributions, and post-surgical distributions were then compared within each subject to compute the mean change in each each measure (*ΔM*) for each subject (*i*), and for each measure (*j*). To compare the outputs from the different measures we computed Spearman's rank correlation between the different measures of *M* (Figure S10), and the area under the receiver operating characteristic curve for each measure.

Figure S10 shows the correlations between the changes in measure (either graph-theoretic, or model-derived) across subjects. The matrix is symmetric about the diagonal. Notice the anti-correlation when using clustering coefficient and betweenness centrality in panel a) – this is to be expected since hub nodes tend to have low clustering (also see e.g. Fig 3 in Hutchings *et al.*, 2015). Also notice the anti-correlation when using node strength and the model (top right square of panel a) - this suggests that highly connected nodes have low escape times and hence the removal of them leads to longer escape times overall. The use of clustering coefficient is also highly correlated with both the use of node strength and use of the model, suggesting the origin of the high strength and low escape time may be due to abnormally high interconnectivity within clusters. Overall, inspecting the absolute correlation shows only a partial relationship between each of the graph theoretic metrics and the model – suggesting complementary information may be gained through use of the model, in addition to aiding interpretation in the context of epilepsy.



**Figure S10. Similarity between mean change following random- and actual-simulated resection using different measures.** Changes in different network measures correlate with each other and the model. The changes in clustering coefficient and strength have the highest similarity with the model suggesting the model predictions may be driven by disruptions to highly clustered, strongly connected local networks.

Table S10 shows the AUC of the ROC curve using the different network measures, including our model. Interestingly the clustering coefficient performs very well with an AUC of 0.89. The clustering coefficient is also very strongly correlated with the model predictions. This suggests that this aspect of the network may be driving our positive modelling results. Measures of hubness such as betweenness and eigenvector centrality perform less well, whilst node strength is comparable to the model.



These results using CC suggests hyperconnectivity in local areas (high local clustering), which when disrupted by the removal of highly clustered nodes, may be driving the results we observe. This leads to the intriguing possibility that alternative ways to disrupt high local

clustering in networks may lead to fewer seizures. One way to do this may be through incision (e.g. using multiple subpial transections), rather than complete resection. Surprisingly, the CC has a better predictive value than all other measures, including our model with an AUC of 0.89, as compared to 0.84 for the model. However, this difference amounts to a better classification of two subjects and a misclassification of one subject which was previously correct using the model (this means one better classification overall). Future studies should investigate if this difference is robust and significant for larger datasets and if the CC and Model can be used together to improve prediction. Interestingly, two of the measures of network centrality (BetC, EigC) have less success, suggesting locally clustered subnetworks, as opposed to globally important network hubs drive the genesis of seizures in our model. The good accuracy of strength as a predictor may be reflecting the high interconnectivity of the local clusters. This is in agreement with other modelling studies of spatially constrained spreading in modular networks (see e.g. Kaiser *et al.*, 2007) where in those modular networks, had increased clustering within modules.

#### **Supplementary References**

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