This document will contain summary of selected papers I read.

[*Yokota et al.*, 2016] reported the seafloor geodetic observation network data and an offshore interpolate slip-deficit rates (SDRs) distribution model. They use the seafloor geodetic data to invert the SDRs in Japan, and get a model that is robustly similar to that obtained in the past studies using only the onshore data. A couple of interesting things:

* Subducting ridge not only activates shallow VLFEs, but also forms the low-SDR region (low-coupling condition)
* These low-SDR region usually is the boundary of the rupture, if the earthquake rupture stops at these boundaries, it maybe a small earthquake, but if it ruptures through, it maybe a large earthquake.

[*Hardebeck and Shelly*, 2016] using templates matching and double-difference to identify and locate the aftershocks for the 2014 Napa Earthquake. They find many aftershocks occur in a complex zone of secondary faulting. They also generate the focal mechanism and most of them show strike-slip and oblique-reverse faulting on secondary dipping faults in the main aftershock zone. These secondary faults were brought closer to failure by Coulomb stress changes from the main-shock. One conclusion is: the lack of stick-slip patches in the southern rupture zone may contribute to the low productivity of the South Napa aftershock sequence.

A new paper in Science in the week of Jun 6th 2016 [*Jiang and Lapusta*, 2016] reports the evidence to answer the question why many major strike-slip fauts known to have had large earthquakes are silent in the interseismic period. They suggest the absence of the microseismcity at the bottom of the seismogenic zone indicates deep rupture past the seismogenic zone in previous large earthquakes. They supporting their hypothesis using observation and numerical simulations. The observations are from 3 earthquakes, the Parkfield M6.0 and the Loma Prieta M6.9, and the M7.5 Denali earthquakes. But I think the observations are not supporting quite well, you do see for Loma Prieta M6.9 seismicity move deeper after the earthquake, for Denali earthquake, they argue there was a large earthquake penetrated deeper before the Denali earthquake, that’s why you don’t see the seismicity before or after the earthquake. I don’t buy it. The conclusions come from numerical simulations of fault behavior looks fine, they compared two models M1 and M2, which M1 only rupture in the seismogenic zone, but M2 rupture into the deeper creeping section. You do see the microseismicity stop after the rupture in M2, which support their hypothesis.

[*Zaliapin and Ben-zion*, 2015] try to classify the induced seismicity and natural seismicity using statistical features of different clusters. They use a metrics that defined the distance between any of the two earthquakes from [*Baiesi and Paczuski*, 2004] to study the difference. The metrics is interesting and can be used as the weight of the nodes in network theory. But this paper is a not easy reading due to the poor writing, a lot of the things are not explained clearly!

[*Hsu et al.*, 2016] started to build a classification algorithm to distinguish false triggers and true triggers using machine learning algorithms that I long thought to do. See their feature list. But I think their method have some problems that will not working so well in real time.

[*An and Meng*, 2016] try to use array backprojection to do tsunami early warning. What they are doing is to use current EEW system to find the location of the earthquake, and then estimate the rupture area using an ellipse/polygon encloses seismic radiators. The magnitude can be estimated based on the scaling law. Based on the M = uAD, they can then estimate the average slip which is used to feed into the model to simulate the tsunami waves. This is different from Diego’s method [*Melgar et al.*, 2016a] which is estimating the rupture dimension based on the scaling law from the past earthquakes. Then he estimate the average slip based on M = uAD. So they use scaling law to estimate different quantity in the M = uAD equation.

[*Agurto-Detzel et al.*, 2016] reported the spatiotemporal association of the small-magnitude seismic sequence with the collapse of a mine tailings dam in Brazil 2015, mainly from observational from the timing and location of the event. They gave three possible scenarios, 1) The dam collapse was triggered by the ground shaking of the earthquakes, 2) the earthquakes triggered soil liquefaction which in turn caused the dam failure, 3) static liquefaction for which no seismic triggering is needed. They don’t have a final conclusion which caused the failure, but the small earthquakes for sure have a contribution to the failure.

[*Mallard et al.*, 2016] reports on Nature to try to answer the question how the surface of Earth is split into an organized jigsaw of seven large plates of similar sizes and a population of smaller plates whose areas follow a fractal distribution. They did 3-D spherical geo-dynamic modeling and demonstrate that the plate layout of Earth is produced by a dynamic feedback between mantle convection and the strength of the lithosphere. They produce model that consistent with the plate size-frequency distribution observed on Earth, and showed that the subduction geometry drives the tectonic fragmentation that generated plates. The more curvature the trench is, the more triple junction they will have. They also showed the larger plates are an expression of the dominating convection wavelength (longer wavelength generate larger plates), and their fragmentation into smaller plates is driven by subduction geometry.



This is a very nice figure in [*Wu et al.*, 2016].

[*Lee et al.*, 2016] report the two stage rupture of the 2015 M8.4 Illapel Chile earthquake. They use spectral-element method to invert the teleseismic and regional waveforms including P waves, S waves, reflections, and surface waves. They found evidences that there were 3 large asperities, and two distinct rupture processes from the source time function. To support this, they also using empirical green’s function method to get the relative source time function for all azimuths. They provide several hypothesis for the two-stage rupture process. (1) The stress state immediately changed after the first rupture stage, (2) the slip might rebound from the free surface of the fault, (3) the second stage rupture can be considered as a rapid postseismic slip.

[*Melgar et al.*, 2016b] using finite fault modeling and teleseismic backprojection to study the 2015 M8.3 Illapel Chile earthquake. The finite fault model shows two asperity of rupture, a deeper one and a shallow one. The backprojection results show the deeper rupture radiate more high frequency energy, and the shallow asperity radiate more low frequency energy. This paper argues that the high frequency radiated from the deeper part contributes the strong motion, and the low frequency radiated from the shallower part is the main reason to generate tsunami.

[*Porritt and Yoshioka*, 2016] study the 2015 Chichi-jima M8 earthquake using receiver functions. They observe multiple conversions within and below the transition zone, which they associate with seismic waves passing into and out of segments of the subducting Pacific plate. Then they infer slab material is piling up at the base of the transition zone and segments are penetrating into the lower mantle.

[*Yoon et al.*, 2015] develops a new method to detect earthquakes based on the similarity. In this paper, they have a nice comparison of different detection algorithms (good/bad). The biggest advantage of this FAST (Fingerprint And Similarity Thresholding) is the speed, while the disadvantage is the memory usage. So it trades off higher memory requirements in exchange for faster runtime and reduced algorithmic complexity. The algorithm has two components, (1) feature extraction, and (2) similarity search. For the feature extraction, it first calculates the spectrogram, and then using a sliding window to get the spectral image. The next step is to get the top k coefficient from the Haar wavelet transform (only keep the sign), and then encode it to binary fingerprint. After the feature extraction step, it inserts the fingerprint to the hash database, and do similarity search later.

[*Bonnefon et al.*, 2016] conducted surveys show the social dilemma of autonomous vehicles. They found people are like the idea of the more ‘moral’ cars, i.e. to minimize the damage even by sacrificing the passengers. But they don’t want to buy these cars by themselves. Also, people don’t like the regulated way to solve the problem. This paper discusses the potential issues for the self-driving cars, but to me, it seems the sample data sets is too small and biased.

[*Lin et al.*, 2016] reports to nature the results from the NoMelt array. The first removed the infragravity waves and tilt noise, and measured phase velocity of the surface waves to get the azimuthal variation of the phase velocity at different periods (sensitive to different depth). Then they inverted the azimuthal variation of the phase velocity to get the azimuthal anisotropy at depth. From the results, they provide several implications, (1) corner flow at the mid-ocean ridge represents the dominant fabric-forming process in the shallow oceanic mantle. You can see the agreement of the anisotropy with the fossil spreading direction up to about 70 km in depth. (2) they suggest that the strongest deformation is induced by dynamic flow within the asthenosphere, rather than passive shear strain associated with motion of the plate over the underlying mantle. Because there is no anisotropic direction align with the apparent plate motion at all depth, and the pattern of the anisotropic strength with depth (strong – weak - strong). Based on the pattern of the anisotropy with depth, they suggest two scenarios for the dominant geodynamic flow in the central Pacific asthenosphere, Pressure-gradient-driven flow and density-driven small-scale convection. (I need check fossil spreading direction (what’s the relationship with the apparent plate motion), and the corner flow).

[*Benson et al.*, 2016] developed a new generalized framework for clustering networks on the basis of higher-order connectivity patterns. It can be scaled to large networks with billions of edges, moreover, the algorithm can easily be parallelized. This new framework provides new insights into network organization beyond the clustering of nodes based only on edges, so it will be interesting to see the results applied on some of the large network data.

[*Ester et al.*, 1996] report the famous DBSCAN algorithm (Density-Based Spatial Clustering of Applications with Noise). This is a nice algorithm to cluster spatial data based on density. It has two parameters: epsilon and min\_points, the advantage of the algorithm is that you don’t have to specify how many clusters you need, it can find all the clusters that satisfy the requirement. For the disadvantage, it is very sensitive to the parameter you choose. The summary of this algorithm is:

Step 1: For each point in the dataset, first draw an n-dimensional sphere of radius epsilon around the point (if you have n-dimensional data).

Step 2: If the number of points inside the sphere is larger than min\_points, then the center of the sphere can be treat as a cluster, and all the points within the sphere are belong to this cluster.

Step 3: Loop through all the points within the sphere with the above 2 steps, and expand the cluster whenever it satisfy the 2 rules.

Note that, there may be points no belong to any clusters, so just ignore it.

[*Meier et al.*, 2016] reports in GRL the universal initial rupture behavior for earthquakes from M4 – M8. The method he used is to get the PGD time evolution (filter, integrate to displacement, and also scale up the noise level). The time evolution of the PGD is shown in figure2a, and we can see the changes of the behavior of the PGD clear for large and small earthquakes. He also did a Kolmogorov-Smirnor Test, which the null hypothesis is the two samples are from the same distribution. The results of the test is shown in figure2b, he argues that there’s no distinct difference for the small and large earthquakes initiation process. Then he gives the explanation why we see a behavior change in the time evolution for all the earthquakes, i.e. the exponent changes from 3 to 1.5, which he thinks is the transition between the crack-like rupture to the pulse-like rupture. The rupture velocity correspond to this process is accelerating, and then reach a steady state. My opinion (which maybe wrong) about the test in figure 2b is: It looks like before the 0.1-0.2s, we can not distinguish all the earthquakes, but small earthquakes (less than about M5) seems can distinguish from the larger ones start from time 0.2 s after the onset of the P wave. For larger earthquakes, you do need more time to distinguish. But Men is doing this test with the neighboring magnitude bins, if he tries the two bins, i.e. 6.5<M<8 and 4.0<M<4.5, you can use this to argue that with sufficient time (3 or 4 s usually used in EEW is long enough), you can distinguish them.

[*Huang et al.*, 2016] reports the study of the source of the M6.4 2016 Taiwan MeiNong earthquake. In their study, they use seismic data, GPS, and InSAR to try to do a joint inversion to get a view of the source. But they found it is difficult to fit the InSAR data, so they propose there’s a second shallower fault triggered by the slip from the main fault. They use seismic data and GPS data first fit the main fault, and then forward model the deformation, using the residual as the input the grid search the second fault. They found this second fault they found is consistent with some of the previous studies. But the slip of the second fault is not showing on the seismic stations, which they are proposing the slip on this fault is either slow or aseismic. Also, the start time of the second fault is about 3 s after the main shock, which representing travel time of P wave from the main shock hypocenter to the triggered shallow fault. I am a little doubt on this.

[*Nishida and Takagi*, 2016] reports the observation of the S wave from a storm in the Atlantic Ocean using seismic array in Japan. The main method they use is beam-forming in 0.1 to 0.2 Hz frequency window. And they found the P and SV wave energy on the Radial component, and SH wave energy on the Transverse component. They argue the P wave energy is generated by the nonlinear forcing by ocean swell, which can be equivalently represented by a vertical single force on the sea surface, while the observed SV energy maybe from the P-to-SV conversion. The SH wave is generated by the shear traction acting on the sea-bottom horizon, which suggests that the steep topography beneath the source and thick sediments may affect the excitation. They then tried to find source migration of these waves. For P wave, since the energy is strong, what they do is to model the localized excitation source by approximating the source using a vertical single force at a surface point. They then move this force on a grid, and compare the synthetic waveform with the observed waveform, which is similar to Grid MT does. Note that, they also used earthquakes to estimate a station correction term using multichannel cross-correlation, if they don’t do that, the source location will deviate ~300 km. For the SV and SH wave, what they did is to find source location using the back projection method. They conclude that the new observation may gives seismologists a new tool with which to study earth’s deeper structure.

[*Mak and Schorlemmer*, 2016] reports what factors affect people respond to DYFI by examining earthquake and socioeconomic conditions. They use part of the DYFI data (M>4 and ZIP regions with more than 500 residents) and the Census data to form a list of factors, i.e. CDI, Magnitude, Epicentral Distance, Depth, Occurrence Time, Date, Population Size, Percentage of Hispanic Population, Percentage of Educated Population, Percentage of Poor-English-Speaking Population, Percentage of Buildings with Complex Structure, Percentage of Population Living below the Poverty Line, Percentage of Veteran Population, Average Household Size, and Median Population Age. Then they fit a Generalized Linear Model with the number of responses as the dependent variable. I am a little doubt of the method they use, clearly there’re patterns in the residual plot, and like multiple regression, when every you added new Predictor, you always improve your results, that’s also why the coefficients has a lot of the quite small. The other thing is, there’re collinear in the variables, which can make the prediction power down. So I think they still need do a feature selection to get rid of this. Also, clearly the linear model is not a good model for some of the variables. There conclusion is the earthquake factor contributes more to the results, and residents in California and the central and eastern US follow the similar behavior in responding to DYFI.

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